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Three Essays on the US Ready-to-Eat Cereal Industry

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Chen Zhu, Ph.D.

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Previous studies indicate that the current Nutrition Facts Panel (NFP) on packaged foods and beverages may not efficiently provide nutritional information to consumers due to its high information search costs. In October 2007, the food and beverage industry announced the voluntary “Nutrition Key” front-of-package (FOP) system (later renamed as “Facts Up Front” and scheduled to be rolled out officially in 2014). My first chapter uses a market-level natural experiment to empirically evaluate how the voluntary Facts Up Front style FOP labeling system would affect consumer purchasing behavior and dietary choices, and whether the impacts are different across the population in the US Ready-to-Eat cereal (RTEC) market.

In the second chapter, I further study the effects of the Facts Up Front style FOP labels by using a rich data set that combines households weekly purchases, product-level advertising exposure data and detailed cereal products' packaging and nutrition information. Starting with a

market-level discrete choice demand model that allows for consumer heterogeneity and incorporates context effects, I develop an empirical framework for understanding the effects of different labeling schemes on consumers' food choices, market outcomes, manufacturers' product development, and firms' strategic adoption of FOP labels.

In practice, consumers regularly make multiple purchases of different RTEC products in a shopping trip. In the third chapter, I examine the commonly neglected modeling assumption in the existing economic and marketing literature that only one product being purchased in a choice occasion. Existing literature also rarely touches upon the contemporaneous purchasing behavior and usually ignores the underlying correlations among chosen items, which may not be appropriated in studying markets for differentiated storable products such as cereals or carbonated soft drinks. I employ a Multivariate Bayesian approach to study such contemporaneous within-category purchasing behavior and investigate factors that determine the fundamental dependencies among products.

Three Essays on the US Ready-to-Eat Cereal Industry

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To my parents Zhu Yong, Cheng Yaping, and my husband Tao Zhen

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Contents

Chapter 1

Heterogeneity in Consumer Responses to Front-of-Package Nutrition Labels: Evidence from a Natural Experiment

1.1 Introduction

Nutrition labeling has become of increasing public interest to policy makers, consumers, and the food and beverage industry. In 1994, the Nutrition Facts Panel (NFP) was added to the back or side of food packages under the Nutritional Labeling and Education Act (NLEA), to provide nutritional information of foods on a standardized label and to promote healthier food choices. However, studies indicate that NFP may not efficiently provide nutritional information to consumers due to its high information search costs (e.g. hard to be read on supermarket shelves, lengthy back or side description, etc.), nor has it had an impact on the obesity rate in the US (Drichoutis, Lazaridis and Nayga 2005, Kiesel, McCluskey and Villas-Boas 2011). In October 2007, the food and beverage industry announced the voluntary "Nutrition Key" front-of-package (FOP) system (later renamed as "Facts Up Front"), which displays summary nutrient-specific information for both “negative” (calories, sugar, sodium, and saturated fat) nutrients and selected “positive” nutrients (fiber, calcium, protein, vitamins, etc.).

The Facts Up Front style FOP nutrition labels have raised debate between nutritionists and the food and beverage industry. Although the industry states that it is the best to provide consumers with easier-to-read complete nutrition profiles of both “bad” and “good” nutrients of food products, opponents believe that adding “good” components can be misleading or confusing, and make the overall FOP labels inefficient in helping consumers choose healthier alternatives (Nestle and Ludwig 2010). This paper uses a market-level natural experiment to empirically evaluate how these new Facts Up Front style FOP nutrition labels would affect consumer purchasing behaviors and their dietary choices, and whether the impacts vary across the population.

Previous studies have focused on investigating consumers’ valuation and usage to various labeling schemes using data from surveys (Ippolito and Mathios 1990, Kim, Nayga and Capps 2000, Drichoutis, Lazaridis, Nayga, Kapsokefalou and Chryssochoidis 2008, Todd and Variyam 2008, Kiesel et al. 2011), controlled laboratory and field experiments (e.g. restaurants, supermarkets, etc.) (Keller, Landry, Olson, Velliquette, Burton and Andrews 1997, Kozup, Creyer and Burton 2003, Berning, Chouinard, Manning, McCluskey and Sprott 2010, Barreiro-Hurlé, Gracia and De-Magistris 2010, Kiesel and Villas-Boas 2010). However, only a limited number of studies evaluate consumers' consequent changes in purchasing behaviors and dietary choices that are more closely related to their health status. Teisl, Bockstael and Levy (2001) analyze a nutritional labeling experiment and find that consumer behavior is significantly altered, but the changes are not necessarily leading to a consumption of healthier products. Conversely, Mathios (2000) uses the pre- and post-NLEA scanner data and find that the mandatory nutrition labeling has significant negative effects on sales of higher fat salad dressings.

In this study, I investigate consumer responses to the launch of new Facts Up Front style FOP labels in 2007 using actual purchasing data before and after the labeling intervention. This natural experiment enables me to identify impacts of the new FOP nutritional information changes on households' consumption of Ready-to-Eat cereal (RTEC) products through a differences-in-differences (DID) approach. To address potential distributional effects, I employ the quantile differences-in-differences approach and estimate the heterogeneous treatment effects across the distributions of cereal volume consumed, intake of calories, sugar, sodium, and fiber from cereal products, respectively. Using consumers' purchasing data from real store environments eliminates possible bias generated from survey responses and laboratory experiments. Taking advantage of the rich data set containing detailed product characteristics, nutrition and labeling information, media exposure, and households' socio-demographic characteristics, I can control for a number of potentially confounding factors and explore further on how individual characteristics may lead to different responses in labeling change.

To the best of my knowledge, this paper is the first market-level empirical study focused on the impacts of recently employed Facts Up Front style nutrition labels. In particular, I address the following questions: (1) whether the industry introduced nutrition labeling can alter consumers' food choices? (2) do effects differ across different parts of the distribution? (3) how do individual characteristics affect consumers' purchasing decisions as well as labeling intervention responses? and (4) are the new labels confusing or misleading under certain circumstances?

Following a differences-in-differences approach, I find substantial evidence that the new Facts Up Front style FOP labels are generally negatively associated with consumers' cereal volume purchased, intake of calories, sugar, and sodium from cereal products. While quantile differences-in-differences results show that the impacts mainly work on the lower quantiles of the distribution only, or households that purchase less than or equal to two cereal packages per month. It is worth noting that the new Facts Up Front nutrition labels repeat the NFP nutritional information in a new format, hence if consumers have already incorporated the NFP information in their food choices, little impacts would be observed since no additional nutritional information are provided (Teisl, Bockstael and Levy 2001, Kiesel et al. 2011). In other words, consumers' changes in purchasing behaviors in this study can be primarily attributed to the reduced information search costs that the new FOP labels offered.

Additionally, I find that household heads with high school degrees or lower education levels benefit the most from the labeling intervention, and present less calories, sugar, and sodium consumed from cereal products. On the other hand, the new FOP labels could be confusing to this specific subgroup of households in terms of decreasing their consumption of "good" nutrients (fiber) at the same time. The breakfast cereal market also exhibits a successful "kidfluence" of children between age 7 to 17 on their family purchasing decisions of foods.

The remainder of this paper is organized as follows. Section 1.2 introduces the model and empirical strategies. Section 1.3 describes the data. The empirical results of mean impacts and distributional treatment effects are presented in Section 1.4 with robustness verified. Section 1.5 discusses what type of consumers are likely to be affected more by the labeling intervention. Section 1.6 concludes.

1.2 Empirical Strategy

The natural experiment allows me to use a differences-in-differences setup to explore whether the new FOP labels help consumers to make healthier choices of cereal products. To further investigate the heterogeneous effects on households with different socio-demographic characteristics, I implement the quantile differences-in-differences approach which allows the treatment effects to vary across the distribution.

I define the treatment and control conditions in two dimensions to estimate the impacts of the new FOP label systems: (1) by time, and (2) by households' actual purchases of cereal products. First, because both Kellogg's and General Mills' Facts Up Front style labels [1] were launched in October 2007, I expect households have different cereal consumption pattern in the post-treatment period than in the pre-treatment period if the new FOP nutrition labels effectively altered consumers purchasing behaviors. Second, if a household bought a cereal product in a shopping trip that had either Kellogg's or General Mills' new labels on the front of package, the household is considered as "treated". In contrast, households purchased cereal products that did not have such multiple front-of-package nutrition labels are in the control group.

[1] Kellogg's named it as "Nutrition at a Glance" and General Mills named it as "Nutrition Highlights" back then.

To control for the potential serial correlation of shocks that may underestimate the standard errors of treatment effects in a DID set-up, I transform the purchasing data into a pre-treatment and a post-treatment period data (Bertrand, Duflo and Mullainathan 2000, Huang and Yang 2012). Specifically, for each household, I calculate four points: (1) the average pre-treatment monthly cereal consumption from Kellogg's/General Mills, and (2) from Post/Quaker; (3) the average post-treatment monthly cereal consumption from Kellogg's/General Mills, and (4) from Post/Quaker.

The standard differences-in-differences specification is based on the following model:

$$y_{it} = \alpha_0 + \alpha_1 d_{post} + \alpha_2 d_T + \gamma(d_{post} \times d_T) + \tau X + \varepsilon_{it}, \tag{1.1}$$

where y_{it} denotes the average monthly cereal consumption [2] of household i in period t. d_{post} is a dummy variable that equals to 1 for the post-treatment period in the data. d_T is also a binary variable that equals to 1 when household i consumes products from Kellogg's and General Mills. γ is the parameter of interest and the differences-in-differences estimator. X is a vector of control variables, including both marketing mix variables and household demographic variables. ε_{it} is the disturbance term with mean zero and constant variance.

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[2] Measured by a number of different variables: volume of total cereal purchased, demand of calories, sugar, sodium, and fiber from cereal products.

In covariates X, I have the average price and advertising exposure as marketing mix variables. The product promotion variable is defined as the percentage of a particular cereal brand that is under promotion over all observed choice occasions. In terms of demographic variables, I use average age of household heads, a high household income indicator (equals to 1 if a household's income is greater or equal to \$60,000 a year), male and female household heads' educational attainments, household size, and the presence of children among different age groups (under age of 6, between 7 and 12, and between 13 and 17).

To allow for the effects of the treatment and covariates to flexibly vary across the distribution of the dependent variable y_{ij}, I follow Koenker (2005) and estimate the model in equation (1.1) at each chosen quantile. The p^{th} conditional quantile of y_{it} given d_{post}, d_T, and X is:

$$\begin{aligned} q_p(y_{it}|d_{post}, d_T, X) = \alpha_0(p) + \alpha_1(p)d_{post} + \alpha_2(p)d_T \\ + \gamma(p)(d_{post} \times d_T) + \tau(p)X + \varepsilon_{it}(p). \end{aligned} \tag{1.2}$$

Notice that no additional distributional assumptions are made about the error term ε_{it}. The quantile DID estimates can be obtained by minimizing the sum of the absolute residuals in equation (1.2).

1.3 Data

1.3.1 Data Description

For this analysis, I employ three proprietary data sets on household purchases, product-level weekly advertising exposure, and package information for the breakfast cereal category between January 2006 to December 2008 [3]. The Nielsen Homescan data tracks the purchases of breakfast cereal for a panel of 13,985 households across the 16 Designated Market Area (DMAs). These data include purchases made at big box retailers, grocery stores, convenience stores, automatic vending machines and on-line retailers for at-home consumption. For each purchase, I know time and location of the purchase, price and quantity, and other product characteristics such as brand and package size. The Nielsen Media Research data provide brand level TV advertising exposure on a weekly basis for the same DMAs during the same weeks. Advertising exposure is measured in gross rating points (GRPs). I also obtain product package information from the Mintel Global New Products Database (GNPD), which provides detailed product listings since 1996 in 245 categories of food, drink, and other grocery store items. Product listings are collected by Mintel based on product re-

[3] Data and support are kindly provided by the Charles J. Zwick Center for Food and Resource Policy at the University of Connecticut.

formulations, new product introductions, new product packaging, and new product varieties.

I focus on a panel of households who were relatively active buyers of breakfast cereal products during the sample period, and the resulting dataset includes 3,977 households in 16 DMAs [4]. Table 1.1 lists product characteristics of 20 major cereal brands and the four biggest 4 manufacturers, Kellogg's, General Mills, Post and Quaker.

1.3.2 Descriptive Statistics

To verify if there are systematic differences between the treatment and control groups, Table 1.2 compares major household and product characteristics for these two groups. Overall, major demographic and marketing mix variables are substantively similar across the treatment and control group, except that brands in the treatment group have advertising exposure twice as much as those in the control group. This is not surprising considering that the treatment group include cereal products of Kellogg's and General Mills, the nation's two biggest cereal manufacturers as well as advertisers.

Figure 1.1 plots households' monthly cereal products volume purchased of the treatment (Kellogg's and General Mills) and control

[4] "Active buyers" are defined as households who were observed to purchase cereal products at least 10 times during a total of 152 weeks.

(Post and Quaker) groups between November 2006 and September 2008. As this figure demonstrated, the treatment and comparison groups are following very similar trends before the launch of the new FOP systems in October 2007 (vertical dotted line), suggesting that the control group may provide a suitable comparison for the treatment group to study the effects of the new FOP labels on consumer choices.

Figure 1.2 displays a histogram of households' average monthly cereal volume purchased in the sample, with kernel density estimate in the solid blue line. The distribution shows a heavy right tail and strong skewness. Although a majority of households consume about 10 to 50 ounces of cereal products at a monthly level, the long right tail indicates that some households have a very high level of cereal demand. These patterns indicate that the standard differences-in-differences approach of the conditional mean regression, though appropriate to model the mean treatment effect, may be incomplete to describe the full distributional relationship between consumers' heterogeneous cereal consumption and the treatment effect, as well as other covariates. Hence, I use the quantile differences-in-differences approach to capture a more comprehensive picture of how the new FOP labeling system affects different households across the whole distribution, which is robust in handling "outliers" and reduces the importance of functional-form assumptions (Meyer, Viscusi and Durbin 1995, Athey and Imbens 2002).

Figure 1.3 top panel shows the spread of households' monthly cereal consumption estimated at quantiles between the 10^{th} and 90^{th}, from November 2006 to September 2008. The bottom panel gives the quantiles averaged over all months.

1.4 Estimation Results

I begin by discussing estimation results from the standard DID regression specification. I then compare the results with estimates from the quantile DID specification where the treatment effect is allowed to vary over the entire distribution of various dependent variables measuring households' consumption of cereal products.

1.4.1 Mean Impacts from the Standard DID Estimation

Table 1.3 presents standard DID estimation results controlled for major demographic characteristics, marketing mix variables, and DMA fixed effects. Standard errors are obtained from 200 bootstrap replications. The dependent variables from column 1 to 5 are households' average monthly (1) cereals volume purchased, (2) calorie demand from cereals, (3) sugar demand from cereals, (4) sodium demand from cereals, and (5) fiber demand from cereals, respectively.

The DID estimators of *G*T* show that launch of the new labeling scheme is negatively related to households' cereal products volume purchased (column 1), calorie consumption (column 2), sugar consumption (column 3), and sodium consumption (column 4) with significance varies between1% and 5%.

The estimated price coefficients are negative and highly significant in all specifications. On the contrary, advertising exposure of *GRP* has significant positive effects across specifications. I do not find significant impacts of percentage of products under promotion on consumer purchase behavior.

Among all the social-demographic variables, household size, households with annual income of $60,000 and above, households with children between 7 to 12 and 13 to 17, display general positive effects on the dependent variables that are also statistically significant. Household head's age is positively related to cereal volume purchased, calorie and sodium consumed from cereals, but not sugar consumed from cereals, suggesting that younger households have higher incentives to purchase cereals with more sugar. Interestingly, male household heads' with college and graduate school degrees tend to buy more cereal products, consume more calories, sodium, and fiber from cereals. A more detailed examination of impacts on households with different educational attainments is discussed in Section 1.5.

1.4.2 Robustness

To test the robustness of estimated mean impacts of the new FOP labeling, I include clustered standard errors at household level and individual fixed effects to the benchmark regressions discussed in Section 1.4.1. Clustering by households allows non-zero correlation between the errors for different observations of the same household, i.e. controls for common household-level shocks. By further estimating with individual (household) fixed effects, which is equivalent to difference all variables from their means, all unobserved households' differences between treatment and control groups are removed. Results reported in Appendix Table A1.1 and Table A1.2 show that the DID estimates are robust in both circumstances.

1.4.3 Distributional Effects from the Quantile DID Estimation

The standard DID describes the treatment effect on the mean of the dependent variable. However, in the case that the dependent variable has an asymmetric heavy- or long-tailed distribution, the quantile regression is more appropriate than the mean regression (Yu, Lu and Stander 2003). From a policy maker's prospective, it is essentially important to examine whether there are different effects on different sections of the distribution. For example, do households with different levels of cereal consumption respond heterogeneously to the implementation of new FOP labels? If so, given the right-skewed nature of this dependent variable (as shown in Figure 1.2), the standard DID estimation based conclusion and policy suggestions may overlook specific population sections.

In this section, I conduct quantile DID regressions with respect to a variety of dependent variables to explore potential distributional effects of the new FOP labels' implementation. Results on consumers' cereal products volume purchased, calorie consumption, sugar consumption, sodium consumption, and fiber consumption from cereals are reported in Table 1.4 through Table 1.8.

In particular, Table 1.4 give the quantile DID estimation results at the 5^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles of the distribution of households' monthly cereal volume purchased. From the results, households with different levels of cereal demand indeed respond differently to both the new FOP labels and various control variables. The new FOP labels are still negatively and significantly associated with household cereal demand, but only at the quantiles between 0.05 and 0.5 of the distribution. Figure 1.3.(2) demonstrates the quantiles of the dependent variable measured in ounces. The 0.05 to 0.5 quantile corresponds to households' consumption of about 3 to 16 ounces of cereal products per month, which is roughly equivalent to consuming up to two cereal packages in a month. From column 3, the treatment effect is the largest at the 0.5 quantile, or to households that buy about two packages of cereal products per month. The implementation of new FOP labels, however, have little impact on households that consume cereal products at a relatively high level or excessively (column 4 and 5, representing the long right tail shown in Figure 1.2). Figure 1.4 graphically demonstrates the quantile DID effects (as in the solid line) on consumers' cereal volume purchased, where I use 200 bootstrap replications to estimate the sampling distribution and construct 95% confidence intervals (as in dotted lines). For comparison purposes, the mean DID effect is plotted as a horizontal dashed line.

All price coefficients are negative and significant, while price sensitivity increases substantially from the lower quantile to the higher quantile of the distribution. Effects of advertising exposure have increasing positive influences on consumers from the lower quantile to the higher quantile, too. The implication here is that households' with high cereal demand are more price sensitive, and influenced more by advertising.

With regard to the demographic variables, there are clear positive and increasing impacts of the average household head age and household size on cereal consumption through most of percentiles. The presence of children under age of 6 rarely affect households' cereal demand, however, the presence of children between age 13 to 17 show a statistically significant and increasing positive effect. More discussions about demographic issues are in Section 1.5.

Table 1.5, 1.6, 1.7, and 1.8 report similar quantile DID regression results on households' calorie consumption, sugar consumption, sodium consumption, and fiber consumption from cereal products, respectively. The new FOP labels appear effective through all quantiles of the distribution only in the case of reducing sugar intake, as displayed in Table 1.6. For intake of calories and sodium, the new FOP labels only negatively affect households under the 0.5 quantile of the distribution that are similar with the case of total volume demand, as shown in Table 1.5 and Table 1.7. There is no observed significant effects on consumers' fiber intake across the distribution.

1.5 What Types of Consumers Are Affected More?

1.5.1 Education

Previous studies have found positive relationships between education and label usage from survey data (Kim, Nayga and Capps 2001, Drichoutis et al. 2005). This does not necessarily mean that implementation of new FOP nutritional labels would affect higher-educated consumers more and lead to bigger buying behavior changes in real store environments. To further explore how consumers with different educational attainments respond to the Facts Up Front style FOP label changes, I evaluate treatment effects in different subgroups of the full sample.

Table 1.9 gives estimation results of education subgroups, where individual (household) fixed effects are included in the estimation, and only DID estimates from regressions of each *Subgroup* $\times$ *Dependent Variable* combination (30 regressions in total) are displayed. Surprisingly, female household heads with high school degrees and below show biggest influences from the new FOP labels, where cereal volume purchased, calories, sugar, sodium, and fiber consumption obtained from cereal products all associated with negative and significant impacts. The fiber consumption of female household heads with college degrees dose not experience significant changes. On the contrary, female household heads with graduate school degrees, or the highest educational level, are not significantly influenced in any case.

The ineffectiveness to female households with higher educational attainment can be explained by that female consumers who went to graduate schools are already familiar with the nutritional information provided by the new FOP labels, hence less likely to change their food choices from previous experiences. Notice that the Nutrition Facts Panel (NFP) is available on the side or back of all the food products since 1994 [5], which already contains all nutritional information that Facts Up Front labels have. In a previous study, Blitstein and Evans (2006) have shown that only 53% of consumers claim to use NFP

[5] NFP lists detailed nutritional information of total calories, calories from fat, total fat, saturated fat, cholesterol, sodium, total carbohydrate, dietary fiber, sugars, protein, etc, in both quantitative amount per serving and percent of the Daily Value (DV) (Kulakow, Baggett and McNeal 1993).

when purchasing food products, where females and more educated individuals are more likely to use NFP labels (Kiesel et al. 2011). My results highlight the fact that although the new FOP labeling scheme does not affect female households with graduate school degrees much, it effectively helps other female consumers understand and process the nutritional information better, leads to significant decrease in consumption of calories, sugar, and sodium from cereal products, especially to female households with high school degrees and below. The implied reduction in consumer's cost of processing nutritional information may due to the format used to present the new Facts Up Front style FOP labels, which are considerably easier to access and understand compared with NFPs.

For subgroups of male households, impacts are similar to those of female households in general. Except that male households with college degrees exhibit less influences from the launch of new FOP labels.

Additionally, the consumption of fiber, which is regarded as a "good" nutrient, is negatively impacted only in the subgroups of households with high school degrees and below (Subgroup 1 and 4), suggesting that new FOP labels may be confusing to less-educated consumers in terms of distinguishing "good" nutrients away from "bad" nutrients that need to be avoided.

1.5.2 "Kidfluence"

Behavioral studies and marketing research have documented that children can play an important role in influencing their parents and affect family food choices, known as the "kidfluence" (McDonald and Lavelle 2001, Dhar and Baylis 2011, Williams and Page 2011), whereas so far there is little empirical evidence from market level studies or households' actual shopping behavior. On the other hand, little is known about how households with children may respond differently to food nutrition labels. In this section, I provide empirical evidence that the presence of children at different age groups can affect households' dietary choices, as well as responses to the new FOP labels.

The mean DID effects reported in Table 1.3 have shown that the presence of children among two age groups, age 7 to 12 and age 13 to 17, significantly raises households' consumption of cereal products measured in volumes, calories, sugar, and sodium. The coefficients of effects of children between age 13 and 17, *Kids 13 to 17*, are estimated approximately twice as much as that of children between age 7 to 12, suggesting that older teenage children may have an even greater influence on their family food purchasing decisions.

From quantile DID results reported in Table 1.4 through Table 1.8, children at age between 13 to 17 are positively associated with higher household cereal volume purchased, calorie, sugar, and sodium consumption, almost at all percentiles of the distribution. While children at age between 7 to 12 mostly affect only the lowest and highest quantiles.

On the other hand, children under age of 6 seldom have an impact on household cereal consumption, or relate to a negative effect in some cases. This may because that little kids have little influence on their parents' purchasing decisions, or simply due to less food they required as a household member.

To investigate whether households with children belonging to different age groups respond to the new FOP labels differently, I evaluate the treatment effect in each subgroup according to households' children status. The DID estimates are reported in Table 1.10, where individual fixed effects are included in the estimation to remove any other observed or unobserved demographic heterogeneity. Interestingly, households with children between age 7 to 12 and 13 to 17 exhibit significant negative treatment effects after the launch of new FOP labels, compared with little responses in subgroups of households with children under age of 6 or without children under age of 17.

This can be partly explained by potential different overweight/obesity concerns across households of different subgroups. In a recent report, 26.7% of children between 2 to 5 are considered to be overweight or obese in 2009, while for children and teens between 6 and 19, the overweight/obesity rate rises to 33.1% (WIN 2012). Hence, to curb the higher rate of overweight and obesity, families with children between age 7 to 17 may have a special interest in diet, and a higher incentive to search for nutrition information and use nutrition labels (Drichoutis et al. 2005), either by parents or older children themselves.

1.6 Conclusion

In this paper, I analyze whether the implementation of Facts Up Front style FOP labels since October 2007 affect consumers' purchase decisions of breakfast cereals. By using a rich data set from a market-level natural experiment, I am able to estimate the mean labeling impacts on consumers' actual purchasing behavior in real store environments, as well as distributional effects across the population. Based on the differences-in-differences and quantile differences-in-differences approaches, the new FOP labels show strong negative relationships with consumers' cereal volume purchased, intake of calories, sugar, and sodium from cereal products, but the impacts mainly work on households that purchase less than or equal to two cereal packages per month only. Consumers with greater cereal demand (on higher quantiles of the distribution) are more price sensitive, and are less likely to be influenced by the new nutrition information labeling scheme. Since the nutrition information are already available on Nutrition Facts Panels long ago, consumers' changes in food choices can be principally attributed to the reduced information costs provided by the new FOP labels [6].

I further investigate how individual characteristics may determine labeling impacts and consumers' food choices, by taking advantage of the detailed demographic characteristics combining with household scanner data. In general, household size, household head age, and income are positively associated with the consumption of cereal products. The presence of children between age 7 to 12 and 13 to 17 significantly makes their family to consume more cereal products, indicating a successful "kidfluence" in the breakfast cereal market. With Regards to the labeling effects of different subgroups, the largest effect is found among consumers with high school degrees or below. As a result, the new FOP labels are the most successful in terms of helping less-educated consumers interpret nutritional information, make healthier dietary choices, and consume less calories, sugar, and sodium. It is worth noting that, however, household heads with high school degrees or below also exhibit a tendency to consume less fiber after the new labels' launch. This implies that the specific format of Facts Up Front labels, which combines "unwanted" and "wanted" nutrients

[6] Kiesel et al. (2011) show that NFP does not provide nutritional information effectively.

together [7], can be confusing to consumers with lower educational attainment.

This empirical large-scale panel study adds market-based evidence to the existing literature, on how Facts Up Front style front-of-package nutrition labels can reduce information costs, affect purchasing behaviors, and benefit particular consumers in the real store environment. It also highlights the possibility that standard conditional mean regressions may overlook effects on certain parts of the distribution, in which a quantile regression can be more appropriate to examine different distributional labeling impacts. Future research on a variety of food categories may be beneficial to explore potential different responses of consumers to FOP nutrition labels, such as food products that contain a larger taste-nutrition trade-off.

[7] "Unwanted" nutrients include calories, sugar, sodium, and saturated fat; "wanted" nutrients include fiber, potassium, protein, vitamin A, vitamin C, vitamin D, calcium and iron.

Chapter 2

Consumer and Producer Responses to Front-of-Package Nutrition Labeling

2.1 Introduction

Growing concerns on widespread obesity and other diet-related diseases have prompted efforts on getting consumers to eat healthier. Nutritional labeling is a particularly attractive policy instrument because it informs consumers at the point of purchase without being intrusive. The Nutritional Labeling and Education Act (NLEA) in 1994 mandated disclosure of nutritional characteristics for most packaged foods in a standardized form of Nutritional Facts Panel (NFP). There has been a proliferation in recent years in nutritional labeling placed on the front-of-package (FOP), in addition to the back or side-of-package NFP. As FOP nutritional labels are more visible and easier-to-read than the NFP, they have the potential for helping consumers to make informed choices. In addition, it is believed that one of the greatest potential public health benefits of FOP nutritional labeling is to motivate the food industry to develop healthier products and/or reformulate existing products. Golan et al. (2009) suggest that nutritional labeling policies may incite product development and reformulation as the producers strive to appeal to health-conscious consumers, which in turn can improve diet nutritional quality of all consumers including the less health-conscious ones [1]. At the same time, there has also been increasing concern that unregulated FOP nutritional labels could confuse or mislead consumers (Glanz, Hersey, Cates, Muth, Creel, Nicholls, Fulgoni III and Zaripheh 2012, Hawley, Roberto, Bragg, Liu, Schwartz and Brownell 2012).

In response, the Food and Drug Administration (FDA) has undertaken a FOP labeling initiative that calls for cooperative efforts between the government and the food industry in developing a practical, science-based FOP regime (FDA 2010). The White House Task Force on Childhood Obesity concurred (WHTFCO 2010). Congress charged the Institute of Medicine (IOM) to examine the issue. IOM reviewed the existing FOP systems and recommended in a subsequent 2011 report a standardized government-sponsored FOP symbol system focusing on four "negative" nutrients to limit (e.g., sugar) (Wartella, Lichtenstein, Boon et al. 2010, Wartella, Lichtenstein, Yaktine, Nathan et al. 2011). The food and beverage industry, opposed IOM's recommendation and announced its own voluntary "Nutrition

[1] Jin and Leslie (2003) have demonstrated that additional information disclosures of restaurant hygiene grade cards can significantly improve the product quality.

Key" FOP system (later renamed as "Facts Up Front"), just prior to the IOM's recommendations (GMA 2011a, GMA 2011b). Facts Up Front participants would display summary nutrient-specific information for both "negative" nutrients and selected "positive" nutrients (e.g., calcium).

As the government and the industry are still heatedly debating on FOP, it is critical to understand consumers' and producers' responses to different FOP schemes. A number of papers (Grunert and Wills 2007, Glanz et al. 2012, Hawley et al. 2012) surveyed the existing research on FOP nutritional labels. Although there is a growing literature on how consumers perceive and use FOP symbols, most of the studies are based on stated preferences and controlled experiments, and only limited research deals with consumer choices in a real-world setting. Even little research has investigated manufacturers' responses to FOP nutritional labels.

In sum, the existing research offers few insights into the following high-stake questions: How do FOP nutritional labels affect consumer choices in actual shopping occasions? Will food manufacturers voluntarily adopt FOP nutritional labels? What are the effects of FOP nutritional labeling on product development and reformulation? This study attempts to shed light on these issues. Particularly, I develop an empirical framework for understanding the effects of different FOP schemes on consumers' food choices, market outcomes, manufacturers' product development and/or reformulation, and manufacturers' strategic adoption of FOP schemes. Policy makers can use this framework to assess the policy feasibilities and public health benefits of different FOP regimes, and the manufacturers can use it to aid its managerial decision making regarding FOP labels.

I start with a market-level discrete choice demand model that allows for consumer heterogeneity (Berry, Levinsohn and Pakes 1995, Nevo 2000b) (henceforth BLP). As is standard in the literature, a consumer in my model derives utility from a product's attributes including product price, advertising and nutritional characteristics. I further incorporate context effects into the model. Context effects imply that a consumer's choice is influenced by the context provided by other alternatives in the choice set she faces. There is ample documented evidence from psychology and behavioral literature that context effects are important drivers of consumer behavior (Chakravarti and Lynch Jr 1983, Payne 1982, Prelec, Wernerfelt and Zettelmeyer 1997, Ratneshwar, Shocker and Stewart 1987). Incorporating context effects generates more realistic predictions of consumer choices, and thus has important managerial and policy implications. FOP nutritional labeling may impact consumer choices in the following ways in my demand model. First, it could affect consumers' utility derived directly from certain nutrients by increasing the salience of these nutrients. Second, FOP labels may also affect consumers' choices by moderating the relative standing of a product in the choice set or context effects.

I apply the model to the US ready-to-eat (RTE) breakfast cereal market. Ready-to-eat cereals is a staple of American diet. It is the largest packaged food category that is directly marketed to children. The nutrition quality of most of the children's cereals however is poor. Therefore, FOP nutritional labeling in this market could potentially have deep impact from a public health perspective. I combine household purchase scanner data between 2006 and 2008 with detailed on-package information. In late 2007, Kellogg's and General Mills, the two leading companies in this market, individually adopted FOP nutritional labeling systems that summarize the amount of selected nutrients and their respective Guideline Daily Amounts (GDA). This event allows me to identify the effects of FOP nutritional labeling on consumer choices.

With the demand estimates, I turn to the supply side. I investigate the firms' equilibrium strategies of voluntary adoption and product development under various hypothetical FOP schemes, such as "good news only" and "bad nutrients only". For each given FOP scheme, I solve for the profit-maximizing pricing strategy, as well as the equilibrium voluntary FOP adoption strategy for each firm in a simultaneous or a sequential game. Finally, I study a firm's optimal new product strategy under different FOP schemes, taking into account of the context effects. In turn, I examine consumer choices and public health implications resulting from firms' equilibrium strategies.

My empirical investigation finds that nutrient-specific FOP labels have significant influence over consumer choices in the real world. In another word, FOP labels can be an effective way to discourage consumers to limit negative nutrient intake and/or encourage them to increase positive nutrient intake. I also find that, left unregulated, profit-maximizing firms prefer "good news only" FOP label schemes, resulting in high levels of consumption of negative nutrients by consumers. But a FOP scheme that requires disclosure of negative nutrients but allows for that of positive nutrients could be politically viable and leads to "second-best" public health outcomes. Additionally, I present interesting results on new product development under various FOP regimes when context effects are accounted for.

The remainder of the paper is organized as follows. I will complete the introduction with a discussion of some related literature. Then I turn to the empirical avenue: the US RTE market and the data used in the study. Next, I specify the model and discuss identification and estimation methods. Finally I present my results from the demand side and the supply side before I conclude.

2.1.1 Related Literature

There has been an emerging literature on consumers response to FOP nutritional labels, as FOP nutritional labeling has become a hot topic worldwide in recent years. A lot of this literature concerns the cognitive mechanisms through which consumers process, perceive, and prefer different types of FOP symbols and labels, and how consumers from different subpopulations are likely to use FOP symbols when shopping for foods. The primary methodology used includes laboratory experiments and consumer surveys. For instance, Borgmeier and Westenhoefer (2009) use randomized choice experiments to examine how different FOP label formats affect food purchase and consumption. Whereas this type of research is very instrumental in guiding the design of a user-friendly FOP system, it could be low in external validity because it abstracts away many other confounding factors when consumers make their food choices in there real world. Only a handful studies use real-world data to gauge consumer responses to FOP labels and shelf nutritional labels in a realistic setting with inconclusive results. Sacks, Rayner and Swinburn (2009) use sales data of two food categories from a major U.K. retailer in the four weeks before and after the introduction of Traffic Light (TL) FOP labels in 2007. TL is a color-coded system of FOP labels recommended by the U.K. Food Standards Agency (FSA) indicating the level of fat, saturated fat, sugar and salt. A red, amber, or green light indicates a high, medium, or low level of a nutrient, according to FSA's nutrition criteria. They did not find any significant sales change in the sandwich category. Although they find a slight increase in the sales of ready meal category after the TL introduction, they conclude that there was no connection between the change in sales and the healthiness of the products. Schucker et al. (1992) evaluate a shelf-tag program that identifies products low in sodium, fat and cholesterol, and find significant increases in sales in many categories of tagged products. Sutherland, Kaley and Fischer (2010) use purchasing data of RTE cereals from 2006-2008 from a U.S. supermarket chain. In September 2006, the chain adopted a shelf nutritional tag system called "Guiding Star", which displays zero, one, and two stars to indicate the nutritional quality of a product based on weighted scores for trans fat, saturated fat, cholesterol, sodium, added sugars, and positive nutrients including vitamins and minerals, fiber, and whole grains. They find that the implementation of the system has significant immediate and long-term effects on consumers food purchases. In contrast, Freedman and Connors (2011) collected sales data from a field experiment that combines nutritional shelf tags as well as nutritional education conducted in a campus convenience s-tore, and did not find any significant impacts of the intervention on sales. This current research is, to the best of my knowledge, the first study that uses actual purchase data to examine American consumers' response to FOP labels. Using a structural demand model, my empirical approach is distinct. The structural approach has the advantage of enabling counterfactual simulations on the effects of different FOP regimes on realistic consumer choices.

This study also contributes to a limited body of literature on how food producers respond to various FOP nutrition labels. This literature deals with producers' implementation, product development/reformulation, and market sales. This area of research has important policy implications. Young and Swinburn (2002) evaluate the effects of New Zealand National Heart Foundation's Pick the Tick program on product reformulation. Food manufacturers are able to display the Pick the Tick logo on FOP if their products meet certain nutrition criteria. Using data on sales and reformulation, they find that the program led to a 61% average sodium reduction in the breakfast cereal, followed by a reduction of 26% and 11% in bread and margarine category respectively in a one-year period after the program. Two other studies (Williams, McMahon and Boustead 2003, Cobiac, Vos and Veerman 2010) also document that a similar program in Australia is effective in reducing sodium content. Van Camp, Hooker and Souza-Monteiro (2010) use Mintel Global New Product Database to examine FOP voluntary adoptions of all U.K. food releases in 2002-2008. They observe selective FOP adoptions across companies and categories, and find that Guideline Daily Allowance (GDA) FOP system is more widely adopted than the traffic light labeling system (TLS). Vyth et al. (2010) survey 47 manufacturers in Netherlands to investigate whether joining a FOP logo program "Choice" has motivated them to make healthier products. They find that manufacturers respond to the program by developing and reformulating their products to carry the logo. All the existing studies evaluate the producer responses from some implemented FOP symbols. I add to the literature by investigating the sales responses from two implemented FOP systems in the United States. More importantly, I enrich this literature by providing a framework to analyze manufacturer responses to FOP, including voluntary adoption of different FOP regimes, and product development and reformulation decisions.

I study firms' strategic decisions of participating in a voluntary FOP initiative. Therefore, this study is related to the literature on voluntary regulation participation. There has been a number of theoretical literature that consider whether participating in a voluntary pollution-abating initiative can be an equilibrium firm strategy (Brau and Carraro 2011, Dawson and Segerson 2008). The only empirical exception is Cohen and Huang (2012) who develop a dynamic oligopoly model of participation, calibrated with children's RTE cereals also, in a voluntary marketing initiative where participants commit to advertising only products that meet certain nutritional standards. My study focuses on FOP initiatives which involves disclosure of information but not marketing restrictions. My framework can be adapted to analyze voluntary programs of disclosing important product characteristics to consumers.

I specify a demand model that incorporates context effects. Therefore this study is related to the large body of literature on context effects in general, and studies that account for context effects in empirical choice models in particular (Huber, Payne and Puto 1982, Lehmann and Pan 1994, Geyskens, Gielens and Gijsbrechts 2010). I closely follow Rooderkerk, Van Heerde and Bijmolt (2011) in constructing and incorporating context variables. They have shown that accounting for context effects produces better predictions of consumer choices in and out of sample.

2.2 Industry Background and Data Description

My empirical venue is the US Ready-to-Eat cereal market, where Kellogg's, General Mill's, Quaker and Post, together account for more than 75% of sales in the US market between 2006 and 2008 (Figure 2.1). Children's RTE cereals score low in nutrition quality. Reedy and Krebs-Smith (2010) identify children's cereals as a top source of added sugar in children's diet in the US. Using 2008 data, Harris, Schwartz and Brownell (2009a) reports that cereals marketed to children have 85% more sugar, 65% less fiber, and 60% more sodium than adults cereals. Therefore, FOP nutrition labels in this market may bring important public health benefits, given its potential of helping busy parents to make smarter choices and encouraging manufacturers to develop better products.

The major data used for demand estimation consists of household purchase records from Nielsen[2], and detailed product packaging and nutrition information from the Mintel Global New Products Database (GNPD). The weekly purchase data covers seven main Designated Market Areas (DMAs) of New York, Boston, Detroit, Washington D-C, Atlanta, San Francisco, and Seattle between January of 2006 and December of 2008.

For each purchase, I have time and location of the transaction, price paid, quantity, and key demographic variables of the household that made the purchase. I also have product-level television advertising exposure data on a weekly basis for each DMA. The advertising exposure is recorded in gross rating points (GRPs), which measures the size of an audience reached by a specific cereal advertising campaign[3]. In this study, different package sizes of a brand are treated as the same product, and all marketing mix variables are aggregated at brand/DMA/biweekly level to accommodate with the demand model.

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[2] Including purchases made by 13,985 households at big box retailers, grocery stores, convenience stores, automatic vending machines, and on-line retailers for at-home consumption.

[3] GRPs = frequency $\times$ % of target audience reached.

The product characteristics that are assumed to influence consumer tastes include per ounce numerical contents of calories, sugar, saturated fat, sodium, and fiber of cereal products. These variables are then used to construct context variables of compromise and similarity described in the next section. From the Mintel dataset, I am able to define a set of dummy variables that indicate the presence of different nutrition labels on front of cereal packages. Specifically, I have labels of calories, sugar, saturated fat, and fiber that exhibit variation throughout the data period examined.

In October 2007, Kellogg's started to display a monochrome FOP labeling system called "Nutrition at a Glance" based on the European Guideline Daily Amounts (GDA) system on the top-right corner of its cereal packages. Nutrition at a Glance presents the total amount per serving of four key nutrients: calories, saturated fat, sodium, and sugar, along with a percentage of the recommended daily intake values. In addition, Kellogg's can opt to display up to two "nutrients to encourage", such as vitamins and fiber. About the same time, General Mills also started to use a very similar Nutrition Highlights FOP regime. For both companies, the new FOP nutrition labels replace their original FOP symbols and claims which are often vague and qualitative (e.g., "good source of fiber"), without information on actual amount or percentage of recommended daily intake. Figure 2.2 and Figure 2.3 show examples of the front package and FOP symbols before and after the voluntary adoption of GDA type FOP systems for both companies. The two companies with smaller market share in the market, Quaker and Post, did not change their FOP formats throughout the data period. In 2011, the industry proposed that all food and beverage companies use Facts Up Front FOP regime that is almost identical to the ones adopted by Kellogg's and General Mills.

Table 2.1 lists summary statistics of 21 major cereal products investigated in this study. Most of these brands are primarily marketed to children, such as Kellogg's Frosted Flakes and General Mills' Cinnamon Toast Crunch. I also include a number of major family brands such as General Mills' Cheerios and Quakers' Life. Among these products, Kellogg's Frosted Flakes Gold was introduced during my data period and soon recognized as one of the most memorable new product launch in 2008 (Schneider-Associates 2008).

2.3 Empirical Methodology

2.3.1 Demand Model

I start with specifying a random coefficient consumer utility as in BLP (Berry et al. 1995, Nevo 2000b, Dubé, Fox and Su 2012). Suppose I observe $t = 1, ..., T$ markets, the conditional indirect utility of consumer i from purchasing a product $j, j = 1, ..., J$ in market t is given by:

$$u_{ijt} = x_{jt}\beta_i + \xi_{jt} + \varepsilon_{ijt}, \tag{2.1}$$

where x_{jt} contains observed product characteristics, β_i is a vector of individual-specific parameter estimates of consumers' valuation to each product attribute, ξ_{jt} captures unobserved product characteristics of product j in market t, and ε_{ijt} is a mean zero stochastic term distributed independently and identically as a type I extreme value distribution. The consumer can choose an outside option with normalized utility $u_{i0t} = \varepsilon_{i0t}$.

The random coefficient of β_i is given by:

$$\beta_i = \beta + \sigma \nu_i, \tag{2.2}$$

where β measures the mean preference that is common to all consumers, ν_i represents the unobserved household characteristics which assumed to have a standard multivariate normal distribution, and σ is the variance of the random coefficient β_i that is need to be estimated.

Formally, I have the deterministic component of the indirect utility, $x_{jt}\beta_i + \xi_{jt}$, consisting of three terms: a partworth utility (V_{ijt}), label effects (VL_{ijt}), and context effects (VC_{ijt}) (Rooderkerk, Van Heerde and Bijmolt 2011, Geyskens et al. 2010):

$$x_{jt}\beta_i \quad + \quad \xi_{jt} \quad = \quad \underbrace{V_{ijt}}_{\textit{partworth utility}} \quad + \underbrace{VL_{ijt}}_{\textit{label effects}} + \underbrace{VC_{ijt}}_{\textit{context effects}} \quad . \tag{2.3}$$

I incorporate product characteristics (X_j) in the partworth utility for control, including price, advertising exposure, contents of calories, sugar, saturated fat, sodium, and fiber. (Seetharaman 2004):

$$V_{ij} = \beta_i X_j. \tag{2.4}$$

For label effects, I use binary variables of calories, sugar, sodium, and fiber indicating whether a cereal product has numerical labels of these nutrients in the front of package as appeared in labeling systems of Nutrition at a Glance or Nutrition Highlights, interact with numerical value of each specific nutrient (K_j):

$$VL_{ij} = \beta_i^{label} L_j^k K_j. \tag{2.5}$$

To incorporate context effects into the choice model, I specify the contextual component as a linear combination of two context-effect variables, the compromise variable (COMP_j) and the similarity variable (SIMI_j):

$$VC_{ij} = \beta_i^{comp} \text{COMP}_j + \beta_i^{simi} \text{SIMI}_j, \tag{2.6}$$

where I model context effects as the direct utility gain or loss of product j in a choice set S.

Consequently, since ε_{ijt} is defined to have a type I extreme value distribution, by integrating over the set of individual-specific valuations of attributes the conditional probability that consumers would purchase product j in market t can be expressed as:

$$s_{jt}(\delta_t, \sigma) = \int \frac{exp(\delta_{jt} + \mu_{jt}(\nu))}{1 + \sum_{r=1}^{J} exp(\delta_{rt} + \mu_{rt}(\nu))} dP_\nu(\nu), \qquad (2.7)$$

where $\delta_{jt} = x_{jt}\beta + \xi_{jt}$ denotes the mean utility term, and $\mu_{jt} = \sum_k x_{jt}^k \sigma^k \nu_i^k$ represents the individual-specific utility term. In empirical work, the integrals in (2.7) can be evaluated by Monte Carlo simulation. The simulated integrals through N Monte Carlo draws of ν are given by:

$$s_{jt}(\delta_t, \sigma) \approx \frac{1}{N} \sum_{i=1}^{N} \frac{exp(\delta_{jt} + \mu_{jt}(\nu_i))}{1 + \sum_{r=1}^{J} exp(\delta_{rt} + \mu_{rt}(\nu_i))}. \qquad (2.8)$$

2.3.2 Context Variables

Following Rooderkerk et al. (2011), I operationalize the context variables by quantifying the relative positions of cereal products in product attribute space. I consider four key nutrients of cereals: contents of calories, sugar, sodium and fiber. I define the distance between any two products as their Euclidean distance in attribute space by converting numeric product attributes to categorical variables.

The compromise variable is defined as the Euclidean distance (d) between product j and the compromise option M in a specific choice set S:

$$\text{COMP}_j = d_{j,M}. \tag{2.9}$$

M is defined to contain content of each nutrient averaged over all the products in the choice set.

Figure 2.4.(a) demonstrates an example of the compromise variable defined in a choice set of the top 20 cereal products in a three-dimensional characteristic space considering calories, sodium, and fiber only. The point M in the lower-center is the compromise option, each other point denotes a cereal product, and different colors of the points indicating various distances between cereal products to M. By definition, the solid line connecting M and FF is the compromise vector of Kellogg's Frosted Flakes (FF) in this particular choice set. Because the closer that product j to M is, the smaller the distance and the compromise variable COMP_j will be, I expect that the compromise effect in my specification be negative (i.e. negative coefficient of β_i^{comp}).

The similarity variable is defined as the minimum Euclidean distance between product j and product r in the choice set S that they belong to:

$$\text{SIMI}_j = min_{r \in S/\{j\}} d_{j,r}. \tag{2.10}$$

As illustrated in Figure 2.4.(b), from the point of view of Kellogg's Frosted Flakes (FF), the distance between FF and each other product varies from 1 to 6 (as shown in different colors). For the reason that another product of Kellogg's, Lucky Charms, is the closest product to

Frosted Flakes in the three-dimensional attribute space, the similarity vector of Frosted Flakes is the line between *FF* and *LC*. Because the more dissimilar that product j is, the bigger that the similarity variable SIMI_j is, β_i^{simi} is expected to have a positive sign.

2.3.3 Supply Equilibrium

Following (Nevo 2000a), the profits of firm f is given by:

$$\pi_f = \sum_{j \in J_f} (p_j - mc_j) \times M s_j(p) - FC_f, \tag{2.11}$$

where p_j is the price of product j, mc_j is the marginal cost of production which is assumed to be constant (Scherer 1982, Berry, Levinsohn and Pakes 1999, Nevo 2000a), M denotes the market size, $s_j(p)$ is the market share of brand j that belongs to firm f, and FC_f is the fixed cost of production.

By assuming that at equilibrium, each firm is choosing price of each product to maximize total firm profits, i.e. the Bertrand-Nash equilibrium, the equilibrium price must satisfy the following first order conditions:

$$s(p) - \Omega \times \frac{\partial s(p)}{\partial p} \times (p - mc) = 0, \tag{2.12}$$

where Ω denotes the ownership matrix. Consequently, the implied marginal costs are:

$$mc = p - \left[\Omega \times \frac{\partial s_r(p)}{\partial p_j}\right]^{-1} \times s(p). \tag{2.13}$$

2.4 Identification and Estimation

2.4.1 Identification

Price is potentially endogenous, and the solution is to involve instrumental variables in the estimation. In particular, I assume that the demand unobservables (ξ) are mean independent of a set of exogenous instruments, w:

$$E[\xi|w] = 0. \tag{2.14}$$

Following the literature, I use cost shifters of cereal products (price of wheat, firms' advertising expenditure) (Berry et al. 1999, Nevo 2001), products' own prices in different markets (Hausman and Taylor 1981), mean demographic features of markets[4] (household size, presence of children under age of 18)(Romeo 2010), as exogenous instruments for prices. Notice that all the non-price product characteristic variables in X are also valid instruments since they are assumed to be independent of ξ, and this subset is denoted by $\bar{X}$.

In addition, I use a set of optimal instruments to help identify random coefficients and increase efficiency. Chamberlain (1987) shows

[4] See Romeo (2010) for a discussion of the validity of using mean demographics as instruments in BLP models.

that, under conditional moment restrictions, the efficient instruments are the expected values of the derivatives of the conditional moment condition with respect to the parameters. (Berry et al. 1999) propose to use approximations to the optimal instruments for the BLP model. Reynaert and Verboven (2012) compare the performance of the approximation and the exact implementation of the optimal instruments, and demonstrate that both of them can overcome several estimation problems of the BLP model and increase the estimation efficiency and stability substantially.

Formally, suppose the vector of parameters is $\theta = [\beta, \sigma]$, then the set of optimal instruments is given by (Chamberlain 1987, Berry et al. 1999, Reynaert and Verboven 2012):

$$z^{optimal} = E\left[\frac{\partial \xi(\theta)}{\partial \theta} | \bar{X}, w\right] = E\left[\frac{\partial \delta(s, \sigma)}{\partial \theta} | \bar{X}, w\right], \tag{2.15}$$

where δ is the mean utility, s is the market share.

By replacing the expected values of the derivatives in (2.15) with the appropriate derivatives evaluated at the expected value of the unobeservables, I can construct the approximated optimal instruments using the following procedure:

(i) Obtain an initial estimate $\hat{\theta}_0 = [\hat{\beta}_0, \hat{\sigma}_0]$ by using exogenous instrumental variables w.

(ii) Compute the predicted price $\hat{p} = \hat{\alpha}_1\bar{X} + \hat{\alpha}_2 w$ from a first-stage OLS regression, which is also the optimal instrument for price coefficient[5][6].

(iii) Compute the predicted mean utility, $\hat{\delta}_0 = [\bar{X}\ \hat{p}]'\hat{\beta}_0$.

(iv) Compute the predicted market shares, $\hat{s}_0 = s(\hat{\delta}_0, \hat{\sigma}_0)$.

(v) Compute the optimal instruments with respect to σ: $\frac{\partial \delta(\hat{s}_0, \hat{\sigma}_0)}{\partial \hat{\sigma}_0}$.

To summarize, in the estimation I use the complete set of instrumental variables including cost shifters, Hausman-type instruments, mean demographic variables, and Chamberlain-type optimal instruments.

2.4.2 GMM Estimator

The demand model specified in Section 2.3.1 can be estimated using a nonlinear Generalized Methods of Moments (GMM) estimator. I follow Berry et al. (1995) and Dubé et al. (2012) proposed mathematical program with equilibrium constraints (MPEC) approach to estimate parameters of the demand model.

The predicted market shares are restricted to match the observed shares, where δ can be solved from:

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[5] For simplicity, the perfect competition is assumed here. Under Bertrand pricing, $\hat{p}$ can be obtained by repeatedly solving the first order conditions described in (2.12).

[6] The optimal instruments with respect to other parameters in β are the observed product characteristics in $\hat{X}$.

$$s(\delta_t, \sigma) - S_{obs} = 0 \tag{2.16}$$

Let IV be the full set of instrumental variables as described in Section 1.4.1, the moment function is given by:

$$g(\delta) = E\left[IV'\xi\right] = E\left[IV'(\delta - X'\beta)\right] = 0 \tag{2.17}$$

Let A be the GMM weighting matrix and θ be the vector of parameters, the estimated parameters can be solved from the following constrained minimization problem:

$$\min_{\theta,\xi,g} \quad g'Ag, \tag{2.18}$$

$$s.t. \quad s(\delta, \sigma) = S_{obs},$$

$$g = IV'\xi.$$

Notice that the set of instrumental variables during estimation plays a dual role: control for price endogeneity and generate moment conditions to identify random coefficients (Nevo 2012).

2.5 Estimation Results

In this section, I first present demand estimation results and compare outcomes of different specifications. I then conduct various policies and new product introduction simulations to further explore impacts of different labeling schemes on manufacturers and consumers.

2.5.1 Demand Estimates

Table 2.2 presents parameter estimates for different demand specifications: column (1) and (2) are from homogeneous multinomial logit models, column (3) and (4) are from the random coefficient logit model that allows for consumer heterogeneity. I instrument for prices in all four specifications with price of wheat, product level advertising expenditure, prices of products in different markets, household size averaged over each market, and mean household's presence of children status averaged over each market. For specification (3) and (4), a set of optimal instruments as described in Section 2.4.1 is also used to help identify the random coefficients and improve estimation efficiency. All of first stage F statistics exceed 10, indicating that the price instruments are relevant in all specifications. The Hansen J statistics and p-values suggest that there is no evidence that the price instruments are correlated with unobserved demand shocks.

All specifications have the partworth utility for control, including products' prices, advertising exposure, contents of calories, sugar, saturated fat, sodium and fiber. DMA and month fixed effects are also included. Specifically, column (1) has context variables of compromise and similarity effect, and their interactions with the new labeling system that Kellogg's and General Mills employed in 2007. Column (2) consists of both individual label effects (nutrient labels interacted with numerical contents) and context effects. Column (3) contains individual label effects, context effects, and interaction terms of context effects with new labels to capture potential labeling effects on context variables. Column (4) is similar to (2), except that all the parameters are random and allow being different across consumers.

Parameter estimates on prices in all specifications are negative and highly significant. Advertising exposure has a strong positive effect on consumer choices of breakfast cereal products. Estimates on taste parameters suggest that consumers generally have negative preferences on sugar and sodium in cereals. Variances of sugar and fiber are estimated to be significant in specification (4), implying a large deviation in distribution of how consumers value sugar and fiber in cereal products.

Both the compromise effect and the similarity effect are statistically significant with expected signs in all specifications, which indicate that context effects do influence consumers' choices in choosing cereal products in a way that described in Section 2.3.2. Interestingly, in specification (1), the interaction terms of the new FOP label and context variables are also statistically significant, suggesting that the new labeling scheme can affect consumer behavior by fortifying context effects.

Estimated label effects of different nutrients are of special interests in evaluating the impacts of Kellogg's Nutrition at a Glance and General Mill's Nutrition Highlights on consumer purchase behaviors in this paper. In specification (4), the estimated label effects of sugar is negatively related to consumers' purchase probability, suggesting that the new labels may help consumers avoid high-sugar cereal products. In contrast, the label of fiber has a positive effect on consumer purchases. Labels of calories and sodium do not significantly alter consumers' choices on breakfast cereals from the heterogeneous specification in column (4).

2.5.2 Price Elasticities, Marginal Costs, and Margins

Table 2.3 reports the estimated own-price elasticities, marginal costs, and price cost margins (PCM $= \frac{p-mc}{p}$) obtained using specification (4) in Table 2.2. Marginal costs are recovered by using Nash-Bertrand equilibrium as described in Section 2.3.3. Consistent with Nevo (2001), I also find that between two similar products, Kellogg's Froot Loops and Post's Fruity Pebbles, the one with higher market share has lower cost [7].

The demand model predicts an average price cost margin of 38% of popular cereal products in the US market between 2006 to 2008. Nevo (2001) shows an average predicted PCM of 45% of the cereal industry using IRI data from 1988 to 1992. The difference in estimated margins can be explained primarily by the industry-wide price cuts in 1996, which leaded to a significant drop in PCM thereafter (Cotterill, Putsis and Dhar 2000, Price and Connor 2003).

2.5.3 *Policy Simulation and Comparison*

A major advantage of using a structural demand model discussed in previous sections is that it allows researchers to handle counterfactual predictions and outcomes. To further investigate how different FOP labels may affect consumer purchases of cereal products, I conduct policy simulations under five different labeling situations.

In particular, I first simulate consumers' response when all of the current FOP labels removed from cereals in Scenario 0. Then I simulate an opposite situation when all the products employ the Facts Up Front type labeling scheme in Scenario 2. Notice that in current prac-

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[7] Shares of Froot Loops and Fruity Pebbles are 1.28% and 0.71% respectively as shown in Table 2.1.

tice (Scenario 1), only Kellogg's and General Mills are using that FOP label, Post and Quaker are not. In Scenario 3 and 4, I simulate situations when only "bad" or only "good" nutrients are allowed to appear on front of packages of cereals, respectively.

After obtaining simulated market shares and prices of each scenario reported in Table 2.4, the predicted payoffs of each firm under different scenarios are calculated and present in Table 2.5. Firms' payoffs are measured by yearly gross profits in an average market. Specifically, compared with Scenario 0 of no FOP labels for all firms, by employing the new FOP labeling system of both "bad" and "good" nutrients in Scenario 2, the gross profits of Kellogg's, General Mills and Quaker have increased up to 0.7 million dollars per year in an average DMA, although they may lose market shares of certain brands in their product portfolios. When firms are only allowed to show "bad" nutrients on front of packages as in Scenario 3, only Kellogg's receives higher profits. On the contrary, firms reach the highest levels of predicted profits when they only display FOP labels of "good" nutrients in Scenario 4.

Given Kellogg's and General Mills' current labeling schemes, I examine potential labeling strategies of Post and Quaker. For both firms, they can choose to either (1) not participate and remain with existing labels; or (2) participate and use Facts Up Front style FOP labels similar to Kellogg's and General Mills. Table 2.6 summarizes expected payoffs of Post and Quaker for both options in a matrix. When the two biggest cereal manufacturers, Kellogg's and Generals, are adopting the Facts Up Front nutrition labels, the strictly dominant strategy for Post is to not employ the new FOP labels.

Predicted effects on consumers' intake of different nutrients are reported in Table 2.7. In particular, compared with the scenario that none of cereal products have the new FOP labels on their front of package (S0), the per capita yearly consumption of calories, sugar, and sodium obtained from cereals drops by 8%, 10%, and 6% respectively because of the adoption of the new labels as shown in Scenario 2. Meanwhile, the per capita intake of fiber increases by 16%. Although the improvements in terms of changing consumers' nutrient composition from diets are limited, we can see that the new Facts Up Front style FOP labels are working on the right track. Consumers' intake of calories, sugar, and sodium can be further reduced by restricting the FOP label of fiber as shown in Scenario 3, although consequently fiber consumption reaches the lowest bound. On the other hand, FOP labels of only "good" nutrients lead to the highest consumption of calories, sugar, saturated fat, sodium, and fiber (S4).

2.5.4 New Product Introduction

The rate of new product introductions is high in the US breakfast cereal market, with an average introduction of 10 to 20 new national brands of leading firms each year (Nevo 2000a, Hitsch 2006). In this section, I use demand estimates to simulate how the launch of different new cereal products would affect the existing choice set, and how the impacts would be different under alternative labeling schemes. Specifically, I evaluate scenarios that Kellogg's launches new national brands in five scenario, from the least healthy to the healthiest new product: (1) an "all bad" product - highest calories / sugar / saturated fat / sodium and lowest fiber; (2) an "all bad but with good fiber" product - highest calories / sugar / saturated fat / sodium / fiber; (3) an "all medium" product - median levels of calories/sugar/saturated fat/sodium/fiber; (4) an "all good but with bad fiber" product - lowest calories / sugar / saturated fat / sodium / fiber; and (5) an "all good" product - lowest calories/sugar/saturated fat/sodium and highest fiber. Table 8 summarizes product attributes of the new product in each scenario (N1-N5). I assume that the new product has the average price, advertising exposure, and marginal cost among all the other existing products in Kellogg's portfolio. Product characteristics of existing brands remain the same, except that the compromise and similarity variables are recalculated according to the change in choice set composition. Hence, consumer demand is affected as consumers face a new choice set and new relative position of each product in attribute space measured by context variables. For each new product, I simulate five labeling schemes as described in Section 2.5.3.

Despite the influences of changes in consumers' choice set, I expect that each new synthetic product has additional impacts on existing brands. For example, in N1, the introduction of an "all bad" new product raises values of the compromise option defined in Section 2.3.2 in the new choice set[8], which reduces distances between the compromise option and other cereal products that contain high calories/sugar/sodium. As a result, these unhealthy products may become more attractive and have higher consumer purchase probabilities. On the other hand, the introduction may reduce the minimum Euclidean distance between two products in the choice set, i.e. smaller similarity variables. Products that are most similar to the new product in characteristic space are most likely to be affected negatively. The overall effects of the introduction of the "all bad" product on consumer choices will depend on how consumers value tastes of the new product, the new product's own position, and how it changes relative positions of all the products in the choice set.

Table 2.9 presents market shares before and after introduction of the Kellogg's synthetic new products under current labeling schemes.

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[8] The compromise option M is [calories, sugar, saturated fat, fiber] = [4.29, 3.48, 3.90, 1.48] before and [4.41, 3.55, 4.09, 1.41] after the new product introduction.

Figure 2.5 visually illustrates positions of all five new products in the existing choice set with contents of calories/sugar/sodium as X/Y/Z axis, and contents of fiber marked using different colors. The 21 existing national brands are indicated by small balls. New products are balls marked with labels (N1 to N5), with different sizes representing predicted market shares. It is interesting to see that the "all good" new product in N5 has the dominant share of 4.65%, followed by "all good but with bad fiber" product in N4, "all bad but with good fiber" product in N2, and "all bad" product in N1, whereas the "all medium" product has the lowest predicted share of 1.03% in N3. Although intuitively, the "all medium" product is the closest to the compromise option among all five new products, other new products may benefit even more from similarity effect and consumer taste preferences. Notice that the estimated market share of the "all bad" new product is 1.44% in N1, while the "all bad but with good fiber" new product has a higher share of 1.76% in N2, implying that the positive labeling effect may overcome the negative taste preference of fiber when consumers meet such not-so-healthy new products. The impacts of different new products on existing brands are mixed. Overall, Kellogg's benefit most by introducing the healthiest new product demonstrated in scenario N5.

I further explore effects of new product introduction on firms under different labeling systems as reported in Table 2.10. Numbers highlighted in green indicate the optimal new product introduction of Kellogg's under each labeling scheme (row). For Kellogg's, introducing an "all good" product (N5) produces highest payoffs under current labeling system (S1), when all firms employ Facts Up Front style FOP labels that allow for both "bad" and "good" nutrients (S2), and when all firms only display "good" nutrients (S4); while an"all good but with bad fiber" alternative leads to highest predicted gross profits when firms do not adopt FOP labels (S0) or when "good" nutrients such as fiber are not allowed on front of packages (S3).

Predicted impacts of new product introduction on consumers are presented in Table 2.11. For each nutrient of calories, sugar, saturated fat, sodium, and fiber, numbers highlighted in green show the "healthiest" outcome to consumers of various new products/labeling schemes combinations, and numbers highlighted in red give the least healthy combination. To distinguish sources of changes, all of existing brands are divided into groups of "good" or "bad" depending on whether each specific product meets the industry-led Children's Food and Beverage Advertising Initiative (CFBAI) guidelines of sugar content[9]. As expected, the highest sugar and sodium intake happen when Kellogg's introduces the "all bad" product (N1) and only shows the label of fiber on front of cereal packages (S4), and the highest sat-

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[9] CFBAI allows a maximum sugar content of 38% by weight (CFBAI 2011, Pestano, Yeshua and Houlihan 2011).

urated fat intake appears when the "all bad but with good fiber" new product introduced (N2) under "good-nutrients-only" labeling scheme (S4). However, when Kellogg's introduces a relatively healthy alternative with lowest levels of calories/sugar/saturated fat/sodium (N4), impacts on consumers are mixed: although the intake of saturated fat has the lowest level when firms are all using Facts Up Front style labels with "bad" nutrients only (S3), the intake of calories reaches maximum when firms are only displaying labels of "good" nutrients (S4), and the intake of fiber has the lowest level when only labels of "bad" nutrients are allowed (S3). A healthier new product that contributes to even more consumption of calories than less healthy alternatives implies that the similarity effect (in this case, hurts existing similar "good" products and benefits dissimilar "bad" products) may overcome the compromise effect and lead to unexpected public health consequences[10].

2.6 Conclusion

I study the effects of the recently launched Facts Up Front style front-of-package nutrition labeling system in the ready-to-eat cereal industry. Using a rich data set, I estimate a flexible demand model allowing

[10] Notice that under S4 of good labels only, the calorie intake from existing "bad" products increases from 5376.2 to 5512.2 as moving from the least healthy new product in N1 to the healthiest alternative in N5.

for consumer heterogeneity and deviating from standard choice assumptions by accounting for context effects. My counterfactual policy simulations show that the new FOP labels can improve consumers' consumption of different nutrients. I also find that the food industry in general would benefit from these policies due to mixed changes of price cost margins and consumer preferences over different cereal brands. Additionally, I explore market outcomes of new product development under various FOP regimes when context effects are accounted for, and find that a relatively healthy new product would benefit some existing products that are high in calories/sugar/saturated fat/sodium mainly due to the outperformance of the similarity effect.

This paper is one of the first to contribute to understanding the labeling effects of Facts Up Front style FOP labels by applying market scanner data in a structural demand model. The estimation of the individual label effect and predicted counterfactual policy outcomes could be indicative of policies aimed at markets with similar issues, for example, the carbonated soft drink market.

In addition, this paper adds to the literature by empirically prove that context effects can alter consumer decision-making process in the breakfast cereal market, and the effects can be reinforced with the use of FOP labels. As demonstrated in this study, the proposed structural model incorporated context effects can be easily adapted to examine the effects of new product introduction to an existing choice set by accounting for relative preference changes among alternatives (i.e. different context variables before/after launch of new products).

The current work has some limitations. Because of the computational limitation, I do not model the distribution of consumer preferences as a function of major demographic variables of each market. The current work is also based on static modeling assumptions. Potential sources for future research include exploring labeling effects and context effects on households with different demographic statistics (household composition, household size, age of household head, etc.), and taking into account consumer dynamics, such as stockpiling behavior that may affect consumer decision-making processes.

Chapter 3

Consumer Within-Category Contemporaneous Purchasing Behavior: A Multivariate Bayesian Analysis of the Cereal Market

3.1 Introduction

Consumers choosing two or more different products from the same category in a shopping trip is very common in a differentiated product market, such as when buying carbonated soft drinks or breakfast cereals in grocery shopping trips. Existing economic and marketing literature rarely touch upon this consumer within-category multiple purchasing behavior, and usually ignore the underlying correlations among chosen items. For example, a consumer may buy both Coke and Sprite in a shopping trip to accommodate people's different taste preferences in a party. Or a consumer may purchase both Kellogg's Frosted Flakes and Froot Loops simply because they are both on sale. In this study, I employ a Multivariate Bayesian approach to study such contemporaneous within-category multiple purchasing behavior, by using household level scanner data of the US breakfast cereal market.

Understanding the within-category simultaneous purchases can be attractive for several reasons. First, retailers and manufacturers are interested in knowing the composition of consumers' multiple choices in a store trip and the underlying dependencies among products. Second, the implied within-category "complementary" and "substitute" products can be critical to both managers and policy makers. For example, managers can make use of consumers' joint purchasing pattens of one product to induce purchase of the other products, or rationalize expenditures across subcategories to maximize overall profits. Policy makers may utilize those insights in designing policy interventions, discouraging consumption of a certain segment and encouraging consumption of its substitutes at the same time.

The strategic importance of consumer within-category contemporaneous demand, along with the relative scarcity of existing research, motivates this empirical investigation. In particular, I have the following research goals: (1) modeling the within-category multiple purchase incidence that provides improved estimates of marketing mix variables and unrestricted substitution patterns; (2) isolating correlations of various products in a differentiated product market, and providing a scheme that naturally implies within-category complements and substitutes; and (3) understanding what factors other than standard marketing mix variables (e.g. brand-level price, advertising, etc.) drive consumer contemporaneous purchases and how they can impact those purchasing correlations. For the third goal, I consider three major joint factors, including manufacturer effects, section effects (kids cereals v.s. adult/family cereals), and joint consumer promotion effects that may originate with the retailer (in-store sales) or the manufacturer (coupons).

Previous studies have largely focused on modeling consumers' discrete choices, by assuming that an individual in a shopping trip is faced with a finite set of choices from which only one product can be chosen (common models include the Multinomial Logit Model, Nested Logit Model, Mixed Logit Model, BLP, etc.). Although theoretically multiple choice incidences can be modeled by including all possible combinations, the number of choice situations increases exponentially with the number of available products in the choice set which makes it computationally infeasible[1]. Taking the US breakfast cereal market for example, according to a panel from the Nielsen Homescan which tracks a total of 13,985 households and their shopping records of cereal products made between 2006 to 2008, 81% of households are involved in buying two or more distinct cereal brands in a store trip. As illustrated in Figure 3.1, only 19% of households stick with the traditional assumption of single purchase. In contrast, proportions of multiple simultaneous choices of 2, 3, and 4 cereal products are 30% ,

[1] For example, if there are 10 products in a choice set, the number of all possible choice situations need to be considered is $2^{10} - 1 = 1,023$.

24%, and 14%, respectively. As a results, although the single purchase assumption may be valid in studying consumer behavior of computers, cars, and other durable goods, it may not be appropriate in the context of the cereal market and similar differentiated goods, and can lead to biased estimates of consumers' responses to marketing mix variables, incomplete estimates of substitution pattern, and incorrect managerial predictions (Dubé 2004). .

To allow for multiple choices behavior and obtain more accurate estimates of consumer preference parameters as well as more complete substitution patterns of cereal products, I use a multivariate probit model (MVP) in Bayesian framework and take into account a relatively large number of cereal products in consumers' choice sets (Chib and Greenberg 1996, Chib and Greenberg 1998, Manchanda, Ansari and Gupta 1999, Edwards and Allenby 2003). The MVP model allows a more flexible modeling of the correlation structure and straightforward interpretation of the parameters (Chib and Greenberg 1998). As compared to the Generalized Method of Moments (GMM) and Maximum Likelihood (ML) methods (Hendel 1999, Dubé 2004), major advantages of Bayesian methods are that the Markov chain Monte Carlo (MCMC) methods implemented with data augmentation algorithm can avoid the numerical integration over a multidimensional normal distribution, easily handle a relatively large dimension of a consumer's choices set, and provide unrestricted estimates of the latent normal correlation matrix (Edwards and Allenby 2003), which are especially suitable for analyzing responses in the differentiated breakfast cereal market. In addition, Bayesian approach does not rely on large sample justifications, hence it is particularly useful when the number of observations is limited in the empirical work on products and markets (Berry 2003, O'brien and Dunson 2004).

The simulated posterior means of correlation coefficients are then used to examine the determinants of consumer within-category purchasing correlations. I make the distinction among own- and cross-manufacturer effects, section effects, and joint promotion effects. To the best of my knowledge, this is the first study to investigate how those joint factors can affect consumer contemporaneous purchases of products in a differentiated product market. Thus, a key contribution of this work is to provide insights on how consumers react to various joint marketing mix variables that have been ignored before.

I use a scanner database of 32 national cereal brands over a 3-year period that contains 713,056 observations, which is unique in the literature to date in terms of sample size and choice set dimension. I find substantial evidence that consumers in a shopping trip prefer to buy multiple items not only from the same manufacturer, but also within the same segment. The implications here are: (1) consumers may have a strong firm level loyalty, or there are some unobserved marketing mix features that induce consumers' within-firm multiple choices (e.g. cereal brands from different manufacturers are usually displayed separately on shelves in the supermarket environment, thus creating an in-store firm-level isolation that makes consumers easier to choose products that lie closer and from the same company; (2) it is somewhat surprising that consumers treat cereals across different segments as “substitutes” rather than “complements”, and a pair of children’s cereals have the highest correlation to be purchased together. Additionally, I find that the joint in-store sales and joint manufacture coupons of a pair of products have significant impacts in increasing their joint purchasing correlation, besides the mixed effects of own- and cross-manufacture status and subcategory preferences.

The remainder of this paper is organized as follows: I first introduce the first stage Multivariate Probit Model and the Bayesian estimation procedure in Section 3.2. I then discuss the second stage joint purchasing correlation model in Section 3.3. Section 3.4 describes the data used in this study. The empirical results of MVP demand estimates and correlation regression estimates are presented in Section 3.5, with additional joint promotion simulations. Section 3.6 concludes.

3.2 Model of Contemporaneous Purchases

3.2.1 The Multivariate Probit Model

Suppose we observe $j = 1, ..., J$ products in the market, and $i = 1, ..., N$ individuals. Let y_{ij} denote the observed binary response of household i on product j. In a multivariate probit framework, we model the observed multiple choices $Y_i = (y_{i1}, y_{i2}, ..., y_{iJ})'$ in terms of a vector of latent utilities, $w_i = (w_{i1}, w_{i2}, ..., w_{iJ})'$. X_i is a $J \times k$ covariate matrix that contains k product characteristic variables, such as price, advertising exposure, contents of sugar, sodium, saturated fat, firm dummies, etc. The utility equations for household i in a shopping trip of buying one or more choices from J alternatives can be represented as:

$$w_i = X_i\beta + \varepsilon_i, \tag{3.1}$$

and the link between the observed behavior and the latent utilities of consumers can be expressed as:

$$y_{ij} = \begin{cases} 1, & \text{if } w_{ij} > 0, \\ 0, & \text{otherwise.} \end{cases}$$

We assume that the unobserved factors are distributed jointly normal as:

$$\varepsilon_i \sim \mathrm{MVN}[0, \Sigma], \tag{3.2}$$

where Σ is a $J \times J$ covariance matrix that captures the correlation in purchase utilities among alternatives. Notice that different from a multinomial logit or probit model, here it allows to have more than one products to be purchased simultaneously. In other words, the critical assumption of allowing only one choice from a set of mutually exclusive alternatives in MNL and MNP model has been relaxed.

According to the multivariate probit model, the probability that $Y_i = y_i$, conditioned on parameters β, Σ and covariates X_i, is given by (Dey, Ghosh and Mallick 2000):

$$\begin{aligned}\mathrm{Prob}(Y_i = y_i|\beta,\Sigma) &= \mathrm{Prob}(y_i|\beta,\Sigma)\\ &= \int_{A_J}\cdots\int_{A_1}\phi_J(w_i|X_i\beta,\Sigma)dw_i\\ &= \int_{A_J}\cdots\int_{A_1}\frac{1}{\sqrt{2\pi}\cdot\det(\Sigma)^{\frac{1}{2}}}e^{-\frac{1}{2}\varepsilon_i'\Sigma^{-1}\varepsilon_i}d\varepsilon_i, \quad (3.3)\end{aligned}$$

where $\varepsilon_i = w_i - X_i\beta$, ϕ_J is the density of a J-variate normal distribution, and A_j is the interval:

$$A_j = \begin{cases}(-\infty,0], & \text{if } y_{ij} = 0,\\ (0,\infty), & \text{if } y_{ij} = 1.\end{cases}$$

3.2.2 Priors and Posterior

From a practical perspective, our interest is to focus on the approximate joint posterior distribution of the parameters and latent variables, where we assume prior independence between β and Σ:

$$\overbrace{\pi(\beta,\Sigma,w|y)}^{posterior} \propto \overbrace{\pi(\beta,\Sigma,w)}^{prior} \cdot \overbrace{\pi(y|\beta,\Sigma,w)}^{likelihood}. \tag{3.4}$$

By Bayes' rule, (3.4) can be expressed as

$$\begin{aligned}\pi(\beta,\Sigma,w|y) &\propto \pi(\beta,\Sigma)\cdot\pi(w|\beta,\Sigma)\cdot\pi(y|\beta,\Sigma,w)\\ &\propto \pi(\beta,\Sigma)\cdot\prod_{i=1}^{N}\Big[\phi_J(w_i|\beta,\Sigma)\cdot \mathrm{Prob}(y_i|\beta,\Sigma,w_i)\Big],\end{aligned} \tag{3.5}$$

where

$$\mathrm{Prob}(y_i|\beta,\Sigma,w_i) = \prod_{j=1}^{J}\Big\{I(y_{ij}=1)I(w_{ij}>0)+I(y_{ij}=0)I(w_{ij}\le 0)\Big\}. \tag{3.6}$$

To summarize the posterior distribution, we use the sampling-based Markov chain Monte Carlo (MCMC) approach and augment the parameter space to include the latent variable $w=(w_1,...,w_n)$ as shown above. Notice that by using data augmentation method, all information from the data of y has transmitted to model parameters through w.

Following Rossi, Allenby and McCulloch (2005), a relatively diffuse but proper prior is used in this analysis: $\beta \sim N(0, 100 I_J)$ and $\Sigma \sim IW(J+2, (J+2)I_J)$. And β, Σ and w can be drawn from the following conditional distributions:

$$w|\beta, \Sigma, y \sim \text{Truncated Normal}: \quad N(m, \tau^2) \times [I(y=1)I(w>0) + I(y=0)I(w \leq 0)]; \tag{3.7}$$

$$\beta|w, \Sigma \sim \text{Normal}(\tilde{\beta}, V_\beta); \tag{3.8}$$

$$\Sigma|w, \beta \sim \text{Inverted Wishart}(\nu_0, V_\Sigma). \tag{3.9}$$

The correlation matrix is obtained by specifying the covariance matrix with unit variance, and it empirically measures the deviation from independence between any two cereal products (Edwards and Allenby 2003, Blumgart, Uren, Nielsen, Nash and Reynolds 2011).

3.2.3 MCMC Algorithm

Implementation of the MVP model is adapted from the `rmvpGibbs` function of `bayesm` package in R library (Rossi, Allenby and McCulloch 2005). In particular, after choosing starting values of w_0, β_0, Σ_0, the sampling MCMC algorithm repeats the following steps for a large number of times, $r = 1, ..., R$:

1. Sample w from its full conditional truncated normal distribution:

$$
\begin{aligned}
w_{ij}|w_{i,-j},\beta,\Sigma,y_i \sim N(m_{ij},\tau_{jj}^2) \\
\times [I(y_{ij}=1)I(w_{ij}>0)+I(y_{ij}=0)I(w_{ij}\leq 0)],
\end{aligned}
$$

where

$$
\begin{aligned}
m_{ij} &= x_{ij}'\beta + F'(w_{i,-j}-X_{i,-j}\beta), \\
F &= -\sigma^{jj}\gamma_{j,-j}, \\
\tau_{jj}^2 &= \frac{1}{\sigma^{jj}};
\end{aligned}
$$

2. Sample β from its full conditional distribution: $\beta_1|w_1,\Sigma_0 \sim N(\tilde{\beta},V_\beta)$, where

$$
\begin{aligned}
& V_\beta = (X^{*'}X^* + A)^{-1}, \quad \tilde{\beta} = V_\beta(X^{*'}w^* + A\bar{\beta}), \\
& \Sigma_0^{-1} = C'C, \quad X_i^* = C'X_i, \quad w_i^* = C'w_i, \\
& X = \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix};
\end{aligned}
$$

3. Sample Σ from the Inverted Wishart distribution of $\Sigma_1|w_1,\beta_1 \sim IW(\nu+n,(V_0+S)^{-1})$, where

$$S = \sum_{i=1}^{n} \varepsilon_i \varepsilon_i',$$

$$\varepsilon_i = w_i - X_i \beta.$$

3.3 Model of Purchasing Correlations

Estimated MVP correlation coefficients subsequently become the dependent variable in a second stage regression model linking various joint marketing mix factors to the different joint purchasing correlations. Specifically, the purchasing correlation between brand i and brand j can be modeled as

$$\begin{aligned} C_{ij} = {} & \text{Intercept} + \text{Joint Promotion Effects}_{ij} \\ & + \text{Manufacturer Effects}_{ij} + \text{Section Effects}_{ij} + e_{ij}, \end{aligned} \tag{3.10}$$

where C_{ij} is the estimated correlation coefficient from the first stage MVP model.

Joint Promotion Effects: The breakfast cereal is one of the most heavily promoted food products (Nevo and Wolfram 2002). According to a panel of Nielsen Homescan data that tracks households' purchases of cereal products in 88,029 store trips made between 2006 and 2008, 42% of shopping occasions involves cereal purchases with either store sales or manufacturer coupons. Although a large research effort has been spent on studying the effects of promotions, little is known about how consumers react to within-category joint promotions and how that affect their contemporaneous purchases. Therefore, two types of joint consumer promotions are considered in this study to explicitly evaluate consumers' responses: the retailers' joint temporary store sales (SS) and manufacturers' joint coupons (MC). Figure 3.2 gives marketing examples of these joint promotions. Detailed variable operationalization is presented in Section 3.4.2.

Manufacturer Effects: I use a set of manufacturer dummies to capture observed and unobserved own- and cross-firm characteristics, such as firms' marketing strategies of joint display or advertising, consumer company loyalty, etc. For the 4 leading manufacturers studies in this paper (Kellogg's, General Mills, Quaker and Post), there are 10 pairwise combinations (dummies) available. For example, Kellogg's Frosted Flakes and Special K have the own-firm dummy of "Two of Kellogg's Cereals" equal to 1, and General Mills Cheerios and Quaker Cap'n Crunch have the cross-firm dummy of "One of General Mills Cereals and One of Quaker Cereals" equal to 1.

Section Effects: For the purpose of this study, I classify cereal products into two major sections: those primarily targeted to children, and the others mainly targeted to adults and families. I then have three dummy variables to indicate the section status of a pair of cereals, which can capture consumer section preferences of cereal products, as well as unobserved section-specific attributes (such as policy interventions on children cereals).

Because the dependent variables are estimated parameters from the first stage MVP model, the model residuals may exhibit heteroskedasticity and lead to incorrect standard errors of ordinary least squares (OLS) estimates. Hence, the heteroskedasticity consistent covariance matrix (HCCM) HC3 is included to correct for potential heteroskedasticity and obtain robust standard errors (Long and Ervin 2000). The HC3 estimator provides OLS regression coefficients but calculates standard errors adjusting for both known and unknown forms of heteroskedasticity (Weiss and Reid 2005). The HC3 estimator is given by

$$\text{HC3} = (X'X)^{-1}X'\text{diag}\left[\frac{e_i^2}{1-h_{ii}}\right]X(X'X)^{-1}, \tag{3.11}$$

where e_i is the model residual and h_{ii} represents the diagonal element of the hat matrix.

3.4 Data Description and Measurement

3.4.1 Description of the Data

Two data sets are employed in this study. The Nielsen Homescan data tracks households' purchase records of ready-to-eat cereal products made from 15 major supermarket chains in 7 designated market areas

(DMA)[2] between Jan 2006 and Dec 2008. Figure 3.3 shows the percentage volume sales from those top chains. There are product characteristics information (e.g. flavor, and package), marketing information (e.g. unit price and promotion), location and time information of each purchase. The Nielsen Media Research data contains brand-level TV advertising exposure on a weekly basis matched with the purchase data. Advertising exposure is measured in gross rating points (GRPs), which is defined as $reach \times frequency$ of a give campaign. For example, if a commercial is aired 3 times a week and reaching 50% of the target audience each time, it would have a weekly GRP of 150 ($3 \times 50\%$).

For this study, I pick 32 popular national cereal brands that belong to the top 4 cereal manufacturers: Kellogg's, General Mills, Quaker, and Post. Table 3.1 lists products with their nutritional information, and summary statistics of average prices, advertising GRP levels, and shares. I also categorize all the cereal brands into two groups based on their targeted markets: kids cereals and adult/family cereals. The "Kids" variable in Table 3.1 is a binary indicator that equal to 1 if the cereal product is primarily marketed to children, and equal to 0 if mainly marketed to adults and families. Children's cereals on average contain 85% more added sugar compared with family and adults

[2] 7 DMAs include (New York, Chicago, Detroit, Atlanta, Boston, Hartford, and San Francisco.

ones (Harris, Schwartz, Brownell, Sarda, Weinberg, Speers, Thompson, Ustjanauskas, Cheyne, Bukofzer et al. 2009b).

Households that have a minimum of 10 purchases of cereal products during a period of 152 weeks are selected (not restricted to the 32 brands examined in this study), yielding a total of 3,126 households and a sample of 713,056 observations in the first stage MVP estimation.

3.4.2 Variable Operationalization

Below, I discuss the operationalization of the measures of joint promotions used in the second stage regression. Two types of consumer promotions are of particular interests in this study: retailers' in-store temporary price cuts and manufacturers' coupons.

The joint store sale variable (SS) is defined as the frequency in which two distinct cereal brands are simultaneously on temporary price cuts in sample. For example, if brand i and brand j are on sale in a particular week/DMA/supermarket chain, it accounts for a single joint sale between these two cereal brands. And summing over all week/DMA/supermarket combinations gives the joint store sale variable of brand i and brand j, SS_{ij}[3]. As such, it reflects the intensity that consumers have the opportunity to choose cereals that are jointly on

[3] There are a total of 7,963 week/DMA/supermarket chain combinations in sample.

sale in their shopping trips. Similarly, the joint manufacturer coupon variable (MC) is defined as the frequency that two cereal products are observed to be redeemed together. Table 3.2 reports pairwise frequencies of joint manufacturer coupons (the upper triangle) and in-store sales (the lower triangle) for all 32 cereal products. For example, Kellogg's Frosted Flakes and Mini-Wheats are simultaneously on store sales for 681 times (out of 7,963 total week/DMA/supermarket chain combinations in sample), and this means that 8.6% of Frosted Flakes' store sales are associated with joint promotions of Mini-Wheats.

Cereal products from the same manufacturer or within the same segment are usually promoted together. Table 3.3 lists the summary statistics of joint promotion variables in sample. From the table, Kellogg's products have the highest frequencies of being on promotion together, including both in-store sales and manufacturer coupons, followed by products of General Mills, Post, and Quaker. In terms of different cereal segments, products that primarily marketed to children have the highest joint store sale frequency, as well as joint manufacturer coupon frequency. On the contrary, the segment of adult and family cereals are less seen on sale together in stores, and the least frequency of manufacturer coupons are observed between a kids cereal and an adult/family cereal.

3.5 Results

3.5.1 First Stage Demand Estimates

The proposed first stage MVP model is run for 20,000 iterations with the every 10^{th} draw kept. After choosing a burn-in length of 300 draws, 1,700 draws are retained from the posterior distributions for inference purposes.

Table 3.4 presents posterior means of parameters with 95% credible intervals in parentheses. As expected, price has a negative and significant effect on consumers purchase probability of cereal products. There is a significant, positive effect of advertising exposure targeted to audience above age of 12, but not of advertising exposure targeted to children between age of 2 and 11. This suggests that young kids may have little influences on their family food choices. Brand fixed effects are included to control for both observed (e.g. contents of sugar, calories, sodium, etc.) and unobserved (e.g. product quality, brand loyalty, etc.) market-invariant product characteristics[4]. DMA and quarter dummies capture the city-specific effect and potential seasonality.

Figure 3.4 accomplishes the results by showing histograms of posterior distributions, trace plots, and autocorrelation functions (ACFs) summarized from MCMC draws of major marketing mix variables.

---

[4] If needed, taste parameters can be recovered from brand fixed effects by using the minimum distance procedure described by (Nevo 2001).

3.5.2 Estimated Within-Category Correlation Matrix

Table 3.5 summarizes parameter estimates of the within-category correlation matrix based on the propose MVP model, after controlling for marketing mix variables and brand/DMA/quarter fixed effects. A bold and positive number indicates that the two cereal products are positively related at 5% level and likely being purchased together, while a negative number suggests the opposite way.

The off-diagonal elements in the table indicate that correlations within the cereal category are generally non-zero, with the correlations being quite large for specific pairs of cereal brands. For example, the estimated correlation in purchase incidences between Kellogg's Apple Jacks and Froot Loops has a posterior mean of 0.43 that is significant at 5% level, whereas the estimated correlation between Kellogg's Frosted Flakes and General Mills' Cheerios, both of which are leading brands of each firm, is -0.21.

Figure 3.5 demonstrates the estimated correlation matrix in a heat map, with different colors from red to green representing a negative correlation to a positive correlation. From the heat map, there are more positive correlations between cereal products from the same manufacturer. Surprisingly, products from the same company but different segments (kids cereals v.s. adult/family cereals) are generally negatively correlated. This indicates that consumers, rather than viewing all cereal products from the same manufacturer as consumption complements, only buy cereals that also belong to the same segment for complementary consumption needs. In other words, consumers show a somewhat strong firm level loyalty when making contemporaneous purchases, but their multiple choice behavior seems to be specific within each cereal segment. These different purchasing correlations can be attributed to consumers' segment preferences, company preferences, and the availability of joint promotions among cereal products, which are evaluated in the second stage regression.

3.5.3 Second Stage Estimates

The estimated posterior means of correlation parameters are then used to analyze how they can be impacted by various factors, namely the manufacturer effect, the segment effect, and the joint promotion effect. Table 3.6 presents parameter estimates for different specifications: column (1) contains the joint promotion effect of store sales and manufacturer coupons; column (2) adds the own- and cross- manufacturer effect of Kellogg's, General Mills, Quaker, and Post; column (3) also considers the cereal segment effect within the subcategories of kids products and adult/family products; column (4) explicitly evaluates how joint promotions may have different influences on different segments of cereal brands by including the interaction terms. Notice that firm dummies capture both observed and unobserved manufacture-specific characteristics other than joint promotional status.

Parameter estimates on both of the joint store sales and joint manufacturers coupons are positive and highly significant, from specification (1) to (3). It confirms that joint promotions are positively associated with consumer simultaneous purchases of a pair of cereal products. From specification (2) to (4), own-firm effects are positive and significant, where products of Quaker exhibit the highest correlations to be purchased together, followed by Post, General Mills, and Kellogg's. In contrast, cross-firm parameters show that a pair of cereal products with one from Kellogg's and the other one from General Mills or Post are negatively associated with the purchasing correlation. This is not surprising considering that Kellogg's was the cereal industry leader in the US market between 2006 and 2008, and faced more intense competition from rivals. Hence, Kellogg's had incentives to not only promote its own products together, but also dissipate consumer tendency to buy its product along with its major competitors'.

Effects within segments are strong and positive, in which a pair of kids cereals are the most likely to be purchased together, as shown in specification (3) and (4). Interaction terms in column (4) suggest that joint store sales are more effective to the adult/family subcategory, whereas kids cereals benefit the most from joint manufacturer coupons.

3.5.4 The Joint Promotion Simulations

To further investigate how different joint promotions may affect consumer purchasing correlations of cereals, I conduct simulations under four different joint store sale/manufacturer coupon situations. In particular, I first simulate correlation responses when frequencies of both joint store sales and manufacturer coupons are increased by 20% in scenario 1. Then I simulate in scenario 2 that all promotions are removed. In scenario 3 and 4, I simulate situations when only joint store sales or only joint manufacturer coupons are increased by 20%, respectively.

The predicted average changes in correlation coefficients are summarized in Table 3.7. Specifically, when both promotions are restricted to have 0 frequencies as in S2, the average correlation declines by 0.0525. On the other hand, by raising the frequencies of both promotions by 20% in S1, pairwise correlations inclines by 0.0105 on average. And from S3 and S4, joint store sales and joint manufacturer coupons attribute to increases of 0.0095 and 0.0010, respectively. Figure 3.6 accomplishes the simulation results by presenting the correlation heat maps of Scenario 1 and 2. Compared with Figure 3.5, the increased frequencies of joint promotions can generally raise the purchasing correlation of a pair of cereal products.

3.6 Conclusion

This paper has investigated the consumer within-category simultaneous demand for breakfast cereals, using a rich dataset of household-level purchase records over 3 years. The Bayesian MVP approach relaxes the "single purchase" assumption that is commonly used in discrete choice models, allows consumer contemporaneous purchases to be correlated across different products, and is particularly useful for the data where a large number of alternatives exist as in a differentiated product market. The second stage correlation regressions further explore determinants of consumer within-category joint purchasing behavior, which is a research question rarely been addressed before. Hence, my results should provide valuable insights to both managers and policy makers.

A majority of consumers are found to buy 2 or more cereal products in a single store trip, and they tend to choose alternatives from the same manufacturer, either because of the firm-level loyalty or other unobserved joint marketing strategies. Surprisingly, consumers do not tend to purchase cereals belong to different segments. Instead, they prefer to buy a combination of different children's cereals the most, followed by a combination of different adult/family cereals and a bundle of mix, implying strong segment preferences of cereal products. Besides manufacture effects and segment effects, joint promotions are found to be positively associated with consumers contemporaneous purchasing behavior, either in the form of manufacturers' coupons or retailers' temporary store sales. This suggests an achievable way to promote multiple items simultaneously in a differentiated product market, which has been ignored in previous studies of promotion effects.

There are some potential areas for future research that can extend and improve upon current study. First, consumer heterogeneity is not considered, which can be modeled by adding a lower level to the hierarchical Bayesian framework. Second, I do not quantitatively measure the impacts of joint promotions on consumer simultaneous purchase probabilities, as a consequence, do not provide insight with respect to the market share changes, which may be evaluated in a structural discrete choice model with a relatively small size of choice set. Third, more research is needed to distinguish the short-run and long-run effects of the joint promotions. Also, it would be interesting to see whether current findings can be generalized to other differentiated product markets.

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Table 1.1 Summary Statistics of Top Ready-to-eat Cereals

Firm	Brand	Calories (/oz)	Sugar (g/oz)	Saturated Fat (g/oz)	Sodium (mg/oz)	Fiber (g/oz)	Price ($/oz)	Observed Share
Kellogg's	Frosted Flakes	103	11	0	129	1	0.144	3.03%
Kellogg's	Raisin Bran	90	8	0	162	3	0.128	2.01%
Kellogg's	Froot Loops	110	13	1	132	1	0.170	1.29%
Kellogg's	Rice Krispies	108	3	0	254	0	0.193	1.17%
Kellogg's	Special K Red Berries	103	9	0	199	1	0.204	1.24%
Kellogg's	Apple Jacks	109	12	0	124	0	0.173	0.97%
Kellogg's	Corn Pops	106	13	0	108	0	0.173	0.84%
Kellogg's	Smart Start	102	8	0	154	2	0.176	0.71%
General Mills	Cheerios	103	1	0	186	3	0.188	3.48%
General Mills	Cinnamon Toast Crunch	121	9	0	196	1	0.162	1.90%
General Mills	Lucky Charms	114	11	0	190	1	0.177	1.47%
General Mills	Cocoa Puffs	112	13	0	149	1	0.175	0.88%
General Mills	Reese's Puffs	121	11	0	187	1	0.178	0.70%
Quaker	Cap'n Crunch	113	12	1	209	1	0.148	0.67%
Quaker	Life Cinnamon	104	7	0	134	2	0.144	0.72%
Quaker	Cap'n Crunch Crunchberries	113	13	1	196	1	0.153	0.64%
Quaker	Cap'n Crunch Peanut Butter Crunch	116	9	1	208	1	0.156	0.40%
Post	Honey Bunches of Oats	112	6	0	140	2	0.151	3.39%
Post	Fruity Pebbles	112	12	1	164	3	0.167	0.70%
Post	Cocoa Pebbles	111	12	1	151	3	0.169	0.57%

Table 1.2 Characteristics of Treatment and Control Groups

	Treatment Group	Control Group
Demographic Characteristics		
Average Household Size	3.32	3.44
Average Female Head's Age	42.80	42.23
Average Male Head's Age	41.21	40.68
% of High Income Households ($60,000 and above/year)	55.54	55.71
% of Hispanic Households	10.13	10.67
% of Female Head with College Degree	49.43	49.94
% of Female Head with Graduate School Degree	9.57	9.10
% of Male Head with College Degree	50.92	51.60
% of Male Head with Graduate School Degree	11.27	10.76
% of Presence of Children Under 6	15.89	16.93
% of Presence of Children 7 to 12	30.13	32.98
% of Presence of Children 13 to 17	29.15	31.80
Cereal Product Characteristics		
Average Price Per Ounce ($)	0.17	0.15
Averge Monthly Advertising Exposure (GRP)	357.47	177.30
Averge Monthly % of Promotions	0.43	0.42

Table 1.3 Mean Outcomes and Impacts

Variable	(1) Volume	(2) Calories	(3) Sugar	(4) Sodium	(5) Fiber
T	0.108	11.872	0.358	4.534	-0.777
	(0.411)	(45.217)	(3.061)	(63.005)	(0.739)
G	8.303***	818.721***	67.305***	1,535.771***	6.734***
	(0.538)	(54.233)	(4.504)	(81.741)	(1.010)
G*T	-1.553**	-168.153**	-13.901***	-222.034**	-0.255
	(0.655)	(69.457)	(5.125)	(98.571)	(1.151)
Price	-27.817***	-2,889.798***	-232.834***	-3,961.526***	-55.650***
	(2.429)	(205.579)	(18.290)	(330.213)	(3.958)
GRP	0.011***	1.207***	0.072***	1.706***	0.014***
	(0.003)	(0.307)	(0.022)	(0.396)	(0.005)
Promotion	0.621	169.221	50.117	-282.518	-17.311
	(5.912)	(662.503)	(45.468)	(994.166)	(10.586)
Household Size	0.703***	84.849***	9.812***	117.140***	0.222
	(0.160)	(16.444)	(1.335)	(26.588)	(0.286)
Household Head Age	0.041***	3.342**	-0.676***	7.975***	0.268***
	(0.012)	(1.342)	(0.111)	(2.151)	(0.027)
High Income	0.765**	80.933**	7.780***	126.711***	1.174*
	(0.322)	(32.563)	(2.563)	(46.247)	(0.686)
Kids Under 6	-0.308	-41.652	-8.345**	-83.938	0.798
	(0.420)	(49.136)	(4.043)	(68.718)	(0.826)
Kids 7 to 12	0.781**	97.409**	12.035***	116.266*	-0.397
	(0.375)	(39.694)	(3.506)	(67.548)	(0.615)
Kids 13 to 17	1.528***	180.175***	25.201***	231.829***	0.130
	(0.323)	(42.123)	(3.523)	(63.369)	(0.719)
Male Graduate School	1.137**	114.904**	-5.629	223.307***	4.535***
	(0.547)	(47.793)	(4.386)	(86.545)	(0.995)
Male College	0.552	53.113	-6.513**	118.841**	2.277***
	(0.353)	(37.797)	(2.682)	(59.819)	(0.590)
Female Graduate School	0.453	47.167	-8.855**	97.784	2.100**
	(0.547)	(54.333)	(4.348)	(81.097)	(0.976)
Female College	0.407	42.767	2.881	75.767	1.210**
	(0.326)	(34.160)	(2.859)	(50.354)	(0.587)
Constant	8.956***	950.677***	92.309***	1,432.091***	25.365***
	(2.979)	(340.931)	(25.293)	(517.056)	(5.882)
DMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.4 Quantile Difference-In-Difference Outcomes and Impacts on Volume

Variable	(1) 5%	(2) 25%	(3) 50%	(4) 75%	(5) 95%
T	-0.023	0.040	0.266	0.153	1.281
	(0.060)	(0.180)	(0.295)	(0.587)	(1.743)
G	1.395***	4.702***	7.668***	11.007***	16.233***
	(0.184)	(0.317)	(0.464)	(0.714)	(2.375)
G*T	-0.695***	-0.862**	-1.787***	-1.012	-3.913
	(0.214)	(0.358)	(0.554)	(0.975)	(2.509)
Price	-2.309***	-10.875***	-22.267***	-45.715***	-90.767***
	(0.465)	(1.407)	(1.594)	(3.385)	(8.660)
GRP	0.000	0.005***	0.011***	0.012***	0.031**
	(0.001)	(0.002)	(0.002)	(0.004)	(0.013)
Promotion	0.310	-2.298	1.187	7.906	-9.859
	(1.039)	(3.362)	(4.868)	(8.476)	(25.611)
Household Size	0.009	0.228***	0.648***	1.055***	1.119*
	(0.032)	(0.080)	(0.139)	(0.210)	(0.597)
Household Head Age	0.006***	0.017**	0.007	0.034*	0.126**
	(0.002)	(0.008)	(0.010)	(0.020)	(0.054)
High Income	0.122**	0.598***	0.636**	0.888*	1.101
	(0.057)	(0.185)	(0.285)	(0.459)	(1.261)
Kids Under 6	0.052	0.087	0.028	-1.061	-0.803
	(0.093)	(0.258)	(0.403)	(0.700)	(1.848)
Kids 7 to 12	0.122*	0.262	-0.186	-0.127	4.137***
	(0.068)	(0.197)	(0.337)	(0.616)	(1.363)
Kids 13 to 17	0.144*	0.650***	1.046***	2.369***	3.184**
	(0.075)	(0.197)	(0.349)	(0.607)	(1.541)
Male Graduate School	-0.074	0.425	1.132**	2.220***	3.459*
	(0.099)	(0.343)	(0.468)	(0.791)	(1.926)
Male College	0.111*	0.429**	0.544*	0.423	0.835
	(0.066)	(0.207)	(0.293)	(0.506)	(1.322)
Female Graduate School	0.157	-0.186	0.229	1.088	1.203
	(0.118)	(0.322)	(0.535)	(0.905)	(2.068)
Female College	0.027	-0.105	0.207	1.002**	0.908
	(0.054)	(0.192)	(0.239)	(0.438)	(1.114)
Constant	1.232**	4.555**	7.008***	12.377**	36.196***
	(0.578)	(1.884)	(2.586)	(4.910)	(13.147)
DMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.5 Quantile Difference-In-Difference Outcomes and Impacts on Calories

Variable	(1) 5%	(2) 25%	(3) 50%	(4) 75%	(5) 95%
T	-3.651	1.133	30.515	29.704	138.148
	(6.460)	(20.235)	(31.802)	(65.736)	(177.036)
G	148.579***	483.999***	782.643***	1,095.461***	1,536.150***
	(20.480)	(31.981)	(54.862)	(72.713)	(256.395)
G*T	-81.790***	-81.720**	-170.510***	-126.161	-392.961
	(23.645)	(38.758)	(59.515)	(105.223)	(257.485)
Price	-270.650***	-1,177.468***	-2,428.081***	-4,988.912***	-10,181.860***
	(50.919)	(152.709)	(174.529)	(380.166)	(968.231)
GRP	0.018	0.506***	1.187***	1.415***	3.381**
	(0.112)	(0.169)	(0.256)	(0.400)	(1.419)
Promotion	37.905	-288.946	134.494	1,017.315	-1,283.458
	(109.816)	(367.412)	(487.794)	(883.477)	(2,846.883)
Household Size	1.058	28.042***	78.793***	126.745***	156.553**
	(3.481)	(8.976)	(16.393)	(23.780)	(66.142)
Household Head Age	0.542**	1.291	0.194	3.260	9.344*
	(0.231)	(0.825)	(1.118)	(2.210)	(5.527)
High Income	12.502*	63.499***	65.107**	81.963*	115.024
	(6.524)	(19.725)	(32.637)	(48.068)	(138.765)
Kids Under 6	8.158	15.902	-10.817	-117.623	-118.488
	(10.607)	(28.220)	(44.954)	(72.839)	(194.087)
Kids 7 to 12	12.923*	21.671	-17.968	13.432	507.689***
	(7.751)	(22.836)	(40.672)	(64.711)	(157.804)
Kids 13 to 17	20.725**	73.608***	125.194***	241.109***	368.222**
	(8.194)	(23.105)	(39.839)	(66.348)	(169.845)
Male Graduate School	-6.105	38.662	132.371**	214.511**	39.829
	(11.434)	(35.749)	(55.025)	(93.301)	(227.329)
Male College	11.053	40.606*	53.241*	42.929	-27.704
	(7.154)	(22.073)	(32.263)	(51.793)	(151.512)
Female Graduate School	20.890	-37.790	22.798	144.170	225.831
	(13.053)	(35.015)	(60.310)	(100.589)	(230.663)
Female College	4.386	-10.754	24.594	114.795**	146.091
	(6.271)	(20.595)	(28.398)	(46.705)	(118.731)
Constant	141.736**	533.794***	780.902***	1,266.310**	4,179.152***
	(59.549)	(197.691)	(268.409)	(514.456)	(1,449.838)
DMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.6 Quantile Difference-In-Difference Outcomes and Impacts on Sugar

Variable	(1) 5%	(2) 25%	(3) 50%	(4) 75%	(5) 95%
T	-0.816	0.424	3.239	-0.342	3.328
	(0.612)	(1.487)	(2.836)	(4.692)	(13.371)
G	1.001	21.035***	50.416***	88.042***	182.529***
	(1.204)	(2.648)	(4.204)	(7.237)	(20.547)
G*T	-2.037*	-5.739**	-12.171**	-15.561*	-41.619*
	(1.130)	(2.551)	(5.473)	(8.048)	(23.237)
Price	-29.064***	-88.980***	-168.464***	-366.310***	-672.913***
	(4.772)	(10.348)	(15.914)	(30.970)	(73.902)
GRP	0.010	0.033***	0.056**	0.093***	0.170*
	(0.006)	(0.013)	(0.023)	(0.036)	(0.095)
Promotion	10.579	39.370	87.048**	142.932**	-105.932
	(10.248)	(27.244)	(39.097)	(66.795)	(216.071)
Household Size	0.735**	4.130***	9.132***	13.513***	17.427***
	(0.358)	(0.834)	(1.264)	(2.255)	(5.824)
Household Head Age	-0.101***	-0.308***	-0.604***	-1.042***	-0.729
	(0.026)	(0.060)	(0.086)	(0.157)	(0.481)
High Income	1.483**	4.685***	7.336***	11.334***	10.361
	(0.724)	(1.544)	(2.643)	(4.369)	(11.966)
Kids Under 6	-0.267	-4.079*	-1.975	-16.842**	-11.594
	(1.146)	(2.438)	(3.293)	(6.597)	(17.466)
Kids 7 to 12	1.861**	3.494*	2.514	6.237	42.982***
	(0.872)	(1.910)	(3.646)	(6.470)	(14.699)
Kids 13 to 17	2.301**	10.229***	19.268***	32.230***	66.012***
	(0.989)	(2.112)	(3.193)	(4.995)	(16.748)
Male Graduate School	-1.188	-2.300	-3.585	6.008	-32.337**
	(1.047)	(2.536)	(3.881)	(6.606)	(15.465)
Male College	-0.868	-0.893	-3.120	-5.738	-30.257**
	(0.718)	(1.602)	(2.429)	(4.292)	(12.923)
Female Graduate School	-1.712	-5.004***	-8.108*	-5.924	-13.760
	(1.079)	(1.843)	(4.403)	(6.065)	(17.971)
Female College	-0.084	-1.847	-0.622	3.827	13.002
	(0.703)	(1.370)	(2.402)	(3.905)	(10.732)
Constant	13.329**	24.707*	44.085**	111.137***	394.765***
	(6.153)	(12.882)	(21.510)	(38.877)	(114.125)
DMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.7 Quantile Difference-In-Difference Outcomes and Impacts on Sodium

Variable	(1) 5%	(2) 25%	(3) 50%	(4) 75%	(5) 95%
T	-15.038	0.302	40.591	51.393	134.993
	(10.891)	(30.664)	(48.582)	(91.221)	(263.330)
G	244.270***	841.681***	1,291.398***	2,159.016***	3,279.327***
	(27.843)	(50.063)	(80.694)	(131.478)	(341.417)
G*T	-76.021**	-163.267***	-227.398**	-221.560	-501.108
	(37.103)	(61.864)	(98.135)	(160.601)	(397.310)
Price	-444.755***	-1,624.739***	-3,447.540***	-6,842.233***	-12,854.158***
	(71.581)	(199.501)	(262.409)	(601.546)	(1,400.312)
GRP	-0.019	0.829***	1.877***	1.689**	4.184**
	(0.143)	(0.248)	(0.402)	(0.733)	(1.674)
Promotion	-8.928	-743.827	-46.625	707.404	-3,729.415
	(210.571)	(560.751)	(753.504)	(1,391.859)	(4,191.486)
Household Size	3.039	33.301***	118.976***	193.438***	310.332***
	(6.039)	(12.221)	(24.918)	(34.637)	(90.014)
Household Head Age	1.098**	2.393*	2.398	7.053**	16.803**
	(0.459)	(1.242)	(1.669)	(3.254)	(7.955)
High Income	15.484	85.054***	116.898**	147.650*	111.438
	(12.791)	(30.497)	(47.242)	(79.814)	(190.605)
Kids Under 6	15.690	2.528	-24.761	-203.067	-210.671
	(17.387)	(46.694)	(70.409)	(125.169)	(264.012)
Kids 7 to 12	31.654**	67.232**	-22.526	-61.928	439.883*
	(13.898)	(34.229)	(62.227)	(96.515)	(250.589)
Kids 13 to 17	39.462***	117.166***	186.144***	316.248***	362.088
	(13.797)	(34.027)	(57.860)	(104.746)	(235.728)
Male Graduate School	0.555	49.484	205.658**	429.135***	602.134*
	(20.243)	(48.034)	(85.767)	(137.467)	(328.576)
Male College	26.526**	77.505**	60.432	60.463	194.220
	(13.445)	(33.779)	(45.450)	(86.710)	(192.824)
Female Graduate School	35.519**	-54.139	86.189	105.271	85.324
	(18.064)	(50.448)	(82.759)	(158.733)	(374.304)
Female College	6.127	-16.343	59.250	152.748**	282.622
	(10.808)	(31.614)	(38.056)	(70.955)	(177.128)
Constant	236.596**	883.518***	1,134.557***	2,025.206**	6,299.041***
	(114.036)	(298.286)	(415.363)	(867.371)	(2,145.352)
DMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.8 Quantile Difference-In-Difference Outcomes and Impacts on Fiber

Variable	(1) 5%	(2) 25%	(3) 50%	(4) 75%	(5) 95%
T	-0.211	-0.211	-0.506	-1.883	-2.402
	(0.192)	(0.327)	(0.611)	(1.256)	(3.441)
G	-0.245	2.390***	5.174***	8.027***	14.368**
	(0.255)	(0.493)	(0.868)	(1.625)	(5.610)
G*T	0.228	-0.113	-1.286	0.739	1.275
	(0.320)	(0.637)	(0.954)	(1.849)	(5.003)
Price	-3.539***	-18.067***	-38.145***	-83.259***	-187.771***
	(0.929)	(1.867)	(3.431)	(6.700)	(16.538)
GRP	-0.003**	0.005*	0.014***	0.020**	0.032
	(0.001)	(0.003)	(0.004)	(0.009)	(0.030)
Promotion	-0.849	-2.653	-11.426	-29.115*	-92.164
	(2.957)	(4.894)	(7.723)	(15.439)	(58.160)
Household Size	-0.001	0.149	0.579**	1.067***	0.513
	(0.067)	(0.145)	(0.264)	(0.394)	(0.992)
Household Head Age	0.024***	0.068***	0.124***	0.335***	0.794***
	(0.006)	(0.012)	(0.020)	(0.042)	(0.133)
High Income	0.072	0.842***	1.208**	1.124	1.321
	(0.152)	(0.269)	(0.562)	(0.937)	(2.987)
Kids Under 6	0.469*	0.419	0.288	0.638	2.313
	(0.252)	(0.403)	(0.682)	(1.457)	(3.729)
Kids 7 to 12	-0.001	0.254	-0.613	-1.768	-3.613
	(0.188)	(0.364)	(0.549)	(1.135)	(2.352)
Kids 13 to 17	0.175	0.396	0.465	0.509	-2.446
	(0.189)	(0.346)	(0.665)	(1.123)	(3.031)
Male Graduate School	-0.005	1.515***	3.526***	5.057**	13.868***
	(0.257)	(0.519)	(0.942)	(1.969)	(4.038)
Male College	0.075	0.962***	1.700***	1.780*	6.723**
	(0.180)	(0.358)	(0.547)	(1.027)	(2.942)
Female Graduate School	0.306	0.332	0.603	2.815	6.028
	(0.269)	(0.453)	(0.859)	(1.741)	(4.889)
Female College	0.166	0.261	0.342	1.688*	3.622
	(0.145)	(0.290)	(0.479)	(0.972)	(2.769)
Constant	2.661*	7.084***	19.036***	39.683***	107.110***
	(1.597)	(2.733)	(4.402)	(8.799)	(31.101)
DMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.9 Treatment Effects of Households' Head at Different Educational Attainments

Subgroups	(1) Volume	(2) Calories	(3) Sugar	(4) Sodium	(5) Fiber
(1) Female Head: High School	-3.852***	-398.747***	-35.861***	-568.227***	-3.243**
	(0.893)	(84.829)	(7.565)	(122.768)	(1.407)
(2) Female Head: College	-1.533**	-165.335**	-24.943***	-246.859*	1.195
	(0.738)	(81.641)	(6.803)	(133.951)	(1.369)
(3) Female Head: Graduate School	0.513	55.411	9.908	-79.258	0.331
	(1.941)	(219.778)	(15.797)	(313.466)	(4.012)
(4) Male Head: High School	-4.042***	-423.039***	-38.737***	-662.338***	-3.586**
	(0.837)	(82.783)	(9.433)	(166.336)	(1.732)
(5) Male Head: College	-1.193	-124.421	-19.306***	-171.239	1.548
	(0.752)	(78.275)	(6.762)	(118.227)	(1.412)
(6) Male Head: Graduate School	-1.704	-180.913	-10.857	-246.012	-2.801
	(1.575)	(184.198)	(12.747)	(245.516)	(2.917)

Notes: Results from DID regressions with individual fixed effects to eliminate any other observed and unobserved houshold heterogeneity. Only results of the mean DID estimates (G*T) are shown above. Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.10 Treatment Effects of Households with Children at Different Age Groups

Subgroups	(1) Volume	(2) Calories	(3) Sugar	(4) Sodium	(5) Fiber
(1) Kids Under 6	-0.170	-9.770	2.171	9.000	-0.711
	(0.573)	(68.488)	(5.429)	(97.431)	(0.871)
(2) Kids 7 to 12	-1.202**	-126.125**	-9.131**	-185.710*	-1.347
	(0.503)	(56.819)	(4.238)	(94.987)	(0.847)
(3) Kids 13 to 17	-1.802***	-187.717***	-15.798***	-304.822***	-2.235***
	(0.497)	(62.072)	(4.814)	(81.313)	(0.752)
(4) No Kids Under 17	-0.160	-8.791	-4.920	-2.691	0.166
	(0.410)	(46.968)	(3.941)	(66.771)	(0.840)

Notes: Results from DID regressions with individual fixed effects to eliminate any other observed and unobserved houshold heterogeneity. Only results of the mean DID estimates (G*T) are shown above. Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A1.1 Robustness Regressions of Mean Outcomes with Clustered Standard Errors

Variable	(1) Volume	(2) Calories	(3) Sugar	(4) Sodium	(5) Fiber
T	0.108	11.872	0.358	4.534	-0.777
	(0.286)	(32.822)	(2.298)	(46.521)	(0.482)
G	8.303***	818.721***	67.305***	1,535.771***	6.734***
	(0.483)	(50.724)	(4.142)	(85.836)	(1.162)
G*T	-1.553***	-168.153***	-13.901***	-222.034***	-0.255
	(0.408)	(54.414)	(3.884)	(83.905)	(0.729)
Price	-27.817***	-2,889.798***	-232.834***	-3,961.526***	-55.650***
	(2.282)	(258.713)	(18.881)	(394.414)	(5.004)
GRP	0.011***	1.207***	0.072***	1.706***	0.014**
	(0.003)	(0.289)	(0.022)	(0.486)	(0.006)
Promotion	0.621	169.221	50.117	-282.518	-17.311*
	(4.934)	(605.580)	(50.516)	(823.271)	(10.085)
Household Size	0.703***	84.849***	9.812***	117.140***	0.222
	(0.190)	(21.330)	(1.618)	(33.423)	(0.300)
Household Head Age	0.041**	3.342*	-0.676***	7.975***	0.268***
	(0.016)	(1.748)	(0.170)	(2.619)	(0.035)
High Income	0.765*	80.933*	7.780**	126.711**	1.174
	(0.394)	(47.031)	(3.171)	(61.385)	(0.784)
Kids Under 6	-0.308	-41.652	-8.345*	-83.938	0.798
	(0.472)	(58.754)	(4.937)	(98.299)	(0.947)
Kids 7 to 12	0.781*	97.409*	12.035***	116.266	-0.397
	(0.451)	(54.614)	(4.586)	(77.440)	(0.736)
Kids 13 to 17	1.528***	180.175***	25.201***	231.829***	0.130
	(0.413)	(48.961)	(4.564)	(75.881)	(0.792)
Male Edu Graduate School	1.137**	114.904	-5.629	223.307**	4.535***
	(0.569)	(70.048)	(5.935)	(100.009)	(1.325)
Male Edu College	0.552	53.113	-6.513**	118.841*	2.277***
	(0.386)	(41.135)	(3.234)	(71.696)	(0.751)
Female Edu Graduate School	0.453	47.167	-8.855	97.784	2.100*
	(0.629)	(62.779)	(5.570)	(102.602)	(1.203)
Female Edu College	0.407	42.767	2.881	75.767	1.210
	(0.403)	(37.622)	(3.328)	(59.102)	(0.808)
Constant	8.956***	950.677***	92.309***	1,432.091***	25.365***
	(3.015)	(351.223)	(30.189)	(468.886)	(6.410)
DMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications and clustered at household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A1.2 Robustness Regressions of Mean Outcomes with Individual Fixed Effects

Variable	(1) Volume	(2) Calories	(3) Sugar	(4) Sodium	(5) Fiber
T	-0.645***	-73.856***	-6.582***	-100.162***	-0.975***
	(0.180)	(20.588)	(1.562)	(30.713)	(0.342)
G	0.571**	58.219**	5.655***	83.298**	0.664
	(0.222)	(23.045)	(1.990)	(37.727)	(0.409)
G*T	-1.143***	-116.478***	-11.314***	-166.658***	-1.328
	(0.332)	(37.851)	(3.205)	(58.848)	(1.587)
Price	-15.754***	-1,654.061***	-129.831***	-2,459.105***	-30.380***
	(1.989)	(257.526)	(19.659)	(343.443)	(3.682)
GRP	0.002	0.220	-0.001	0.238	0.019***
	(0.004)	(0.477)	(0.044)	(0.738)	(0.007)
Promotion	-3.588	-423.502	-40.801	-342.005	2.222
	(4.702)	(485.583)	(40.565)	(646.379)	(8.181)
Constant	0.322**	36.881***	3.287***	50.017**	0.487**
	(0.126)	(13.628)	(0.971)	(20.713)	(0.235)
Observations	11,813	11,813	11,813	11,813	11,813

Notes: Standard errors in parentheses calculated using 200 bootstrap replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2.1 Summary Statistics of Top Ready-to-Eat Cereal Products

Firm	Brand	Calories (/oz)	Sugar (g/oz)	Saturated Fat (g/oz)	Sodium (mg/oz)	Fiber (g/oz)	Price ($/oz)	Observed Share (%)
Kellogg's	Frosted Flakes	103	11	0	129	1	0.150	2.98
Kellogg's	Raisin Bran	90	8	0	162	3	0.134	1.94
Kellogg's	Froot Loops	110	13	1	132	1	0.181	1.28
Kellogg's	Rice Krispies	108	3	0	254	0	0.199	1.15
Kellogg's	Special K Red Berries	103	9	0	199	1	0.204	1.29
Kellogg's	Apple Jacks	109	12	0	124	0	0.184	0.92
Kellogg's	Corn Pops	106	13	0	108	0	0.185	0.82
Kellogg's	Smart Start	102	8	0	154	2	0.182	0.64
Kellogg's	Frosted Flakes Gold	101	9	0	173	3	0.148	0.33
General Mills	Cheerios	103	1	0	186	3	0.191	3.91
General Mills	Cinnamon Toast Crunch	121	9	0	196	1	0.167	2.16
General Mills	Lucky Charms	114	11	0	190	1	0.192	1.71
General Mills	Cocoa Puffs	112	13	0	149	1	0.186	0.76
General Mills	Reese's Puffs	121	11	0	187	1	0.188	0.78
Quaker	Cap'n Crunch	113	12	1	209	1	0.151	0.70
Quaker	Life Cinnamon	104	7	0	134	2	0.148	0.65
Quaker	Cap'n Crunch Crunchberries	113	13	1	196	1	0.157	0.65
Quaker	Cap'n Crunch Peanut Butter Crunch	116	9	1	208	1	0.160	0.47
Post	Honey Bunches of Oats	112	6	0	140	2	0.157	3.51
Post	Fruity Pebbles	112	12	1	164	3	0.173	0.71
Post	Cocoa Pebbles	111	12	1	151	3	0.178	0.52

Table 2.2 Parameter Estimates of Demand Models

	Homogenous MNL	Homogenous MNL	Random Coefficient Logit Model		Random Coefficient Logit Model	
	(1)	(2)	(3)		(4)	
Variable			Mean	Deviation	Mean	Deviation
Partworths						
Price	-6.653***	-7.175***	-2.537**	0.558	-8.905***	0.961
	(0.770)	(0.837)	(1.031)	(6.490)	(1.664)	(16.557)
Advertising Goodwill	1.928***	1.824***	1.287***	5.673***	1.780*	12.643***
	(0.090)	(0.092)	(0.502)	(1.107)	(1.002)	(3.729)
Calories	-0.566	-0.735*	-1.470**	0.034	-0.164	0.941
	(0.392)	(0.414)	(0.740)	(3.437)	(1.442)	(3.797)
Sugar	-0.920***	-0.463***	-0.398***	0.087	-0.814***	4.255**
	(0.104)	(0.113)	(0.150)	(3.090)	(0.267)	(1.675)
Saturated Fat	-0.062	-0.192***	-0.524	6.055***	-0.413	1.361
	(0.046)	(0.048)	(1.006)	(1.975)	(0.343)	(2.446)
Sodium	-1.523***	-1.171***	-1.543***	0.065	-0.927*	0.810
	(0.107)	(0.119)	(0.174)	(4.983)	(0.504)	(4.867)
Fiber	-0.354***	-0.184	-0.185	1.414	-0.652	3.614**
	(0.064)	(0.061)	(0.279)	(1.298)	(1.074)	(1.652)
Constant	-0.584	-0.898**	-2.346***	0.143	-2.241**	0.879
	(0.394)	(0.413)	(0.620)	(2.746)	(1.041)	(2.759)
DMA Fixed Effects	Yes	Yes	Yes		Yes	
Month Fixed Effects	Yes	Yes	Yes		Yes	
Label Effects						
Label * Calories		1.721*	0.833	1.694	-0.010	1.025
		(0.941)	(1.360)	(2.224)	(2.614)	(3.092)
Label * Sugar		-1.940***	-1.534***	0.119	-0.634**	3.139
		(0.187)	(0.316)	(3.263)	(0.251)	(2.599)
Label * Sodium		-2.448***	-2.813	0.695	-0.563	3.444
		(0.323)	(2.023)	(5.044)	(3.823)	(3.824)
Label * Fiber		0.492***	0.226	0.264	0.108*	3.338
		(0.109)	(0.550)	(4.604)	(0.058)	(2.564)
Context Effects						
Compromise Variable	-1.449***	-1.527***	-0.973***	0.132	-2.358*	0.852
	(0.159)	(0.152)	(0.259)	(2.277)	(1.308)	(5.780)
Similarity Variable	2.524***	2.761***	2.240***	0.220	2.721***	2.804
	(0.170)	(0.185)	(0.205)	(2.885)	(0.478)	(1.735)
Label * Compromise Variable	-0.205*		-0.007	0.265		
	(0.114)		(1.067)	(8.882)		
Label * Similarity Variable	0.376**		0.190	2.484		
	(0.175)		(1.332)	(5.992)		
Observations	7,787	7,787	7,787		7,787	
First Stage F Statistic	28.596	24.862	15.283		19.283	
p-value	0.000	0.000	0.000		0.000	
Hansen J Statistic	11.385	10.241	142.907		112.241	
p-value	0.077	0.115	0.075		0.109	

Note. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.3 Estimated Own-Price Elasticities, Marginal Costs, and Price Cost Margins (PCM)

Firm	Brand	Own-Price Elasticity	Marginal Cost ($/oz)	PCM (%)
Kellogg's	Frosted Flakes	-2.781	0.064	57.2
Kellogg's	Raisin Bran	-2.544	0.066	50.6
Kellogg's	Froot Loops	-3.345	0.088	51.2
Kellogg's	Rice Krispies	-3.820	0.130	34.7
Kellogg's	Special K Red Berries	-3.878	0.127	37.8
Kellogg's	Apple Jacks	-3.503	0.111	39.6
Kellogg's	Corn Pops	-3.541	0.114	38.7
Kellogg's	Smart Start	-3.462	0.109	39.9
Kellogg's	Frosted Flakes Gold	-2.909	0.096	35.2
General Mills	Cheerios	-3.656	0.132	30.7
General Mills	Cinnamon Toast Crunch	-3.275	0.115	31.1
General Mills	Lucky Charms	-3.747	0.139	27.7
General Mills	Cocoa Puffs	-3.630	0.133	28.6
General Mills	Reese's Puffs	-3.595	0.129	31.0
Quaker	Cap'n Crunch	-2.811	0.087	42.3
Quaker	Life Cinnamon	-2.750	0.084	43.1
Quaker	Cap'n Crunch Crunchberries	-2.969	0.096	38.5
Quaker	Cap'n Crunch Peanut Butter Crunch	-3.007	0.097	39.3
Post	Honey Bunches of Oats	-2.956	0.099	36.9
Post	Fruity Pebbles	-3.296	0.116	32.8
Post	Cocoa Pebbles	-3.381	0.121	32.2

Table 2.4 Predict Market Shares and Prices of Different Scenarios

Firm	Brand	S0: No Label		S1: Current Practice		S2: All with Bad and Good Labels		S3: All with Bad Labels Only		S4: All with Good Labels Only	
		Share (%)	Price ($/oz)	Share (%)	Price ($/oz)	Share (%)	Price ($/oz)	Share (%)	Price ($/oz)	Share (%)	Price ($/oz)
Kellogg's	Frosted Flakes	3.70	0.145	2.98	0.150	2.86	0.160	2.95	0.160	3.69	0.159
Kellogg's	Raisin Bran	1.11	0.127	1.94	0.134	1.63	0.137	0.84	0.138	1.93	0.140
Kellogg's	Froot Loops	1.30	0.178	1.28	0.181	1.13	0.186	1.19	0.187	1.28	0.189
Kellogg's	Rice Krispies	0.91	0.195	1.15	0.199	1.04	0.202	1.17	0.201	0.84	0.207
Kellogg's	Special K Red Berries	0.98	0.198	1.29	0.204	1.09	0.208	1.14	0.208	0.96	0.217
Kellogg's	Apple Jacks	1.03	0.182	0.92	0.184	0.85	0.187	0.87	0.186	1.01	0.197
Kellogg's	Corn Pops	0.83	0.185	0.82	0.185	0.79	0.189	0.72	0.189	0.83	0.197
Kellogg's	Smart Start	0.50	0.180	0.64	0.182	0.54	0.185	0.40	0.187	0.64	0.181
Kellogg's	Frosted Flakes Gold	0.26	0.147	0.33	0.148	0.29	0.149	0.18	0.149	4.72	0.193
General Mills	Cheerios	3.58	0.184	3.91	0.191	3.91	0.193	3.03	0.193	3.35	0.167
General Mills	Cinnamon Toast Crunch	3.03	0.166	2.16	0.167	2.20	0.169	2.32	0.169	2.45	0.192
General Mills	Lucky Charms	2.57	0.189	1.71	0.192	1.72	0.193	1.80	0.192	0.82	0.187
General Mills	Cocoa Puffs	0.83	0.183	0.76	0.186	0.72	0.187	0.76	0.186	0.94	0.191
General Mills	Reese's Puffs	0.86	0.182	0.78	0.188	0.75	0.188	0.78	0.189	0.67	0.148
Quaker	Cap'n Crunch	0.68	0.148	0.70	0.151	0.75	0.146	0.78	0.146	0.83	0.144
Quaker	Life Cinnamon	0.64	0.145	0.65	0.148	0.65	0.143	0.49	0.143	0.63	0.155
Quaker	Cap'n Crunch Crunchberries	0.63	0.155	0.65	0.157	0.67	0.153	0.71	0.153	0.46	0.158
Quaker	Cap'n Crunch Peanut Butter Crunch	0.48	0.158	0.47	0.160	0.53	0.156	0.55	0.156	3.19	0.155
Post	Honey Bunches of Oats	2.75	0.156	3.51	0.157	2.35	0.155	2.00	0.155	0.85	0.172
Post	Fruity Pebbles	0.60	0.173	0.71	0.173	0.73	0.171	0.53	0.172	0.64	0.177
Post	Cocoa Pebbles	0.45	0.177	0.52	0.178	0.58	0.176	0.40	0.176	0.37	0.149

Table 2.5 Predicted Firms' Yearly Gross Profits In An Average Market ($1,000,000)

	S0: No Label	S1: Current Practice	S2: All with Bad and Good Labels	S3: All with Bad Labels Only	S4: All with Good Labels Only
	Gross Profit	Gross Profit	Gross Profit	Gross Profit	Gross Profit
Kellogg's	10.4	10.9	11.1	10.5	13.0
General Mills	6.8	6.8	7.0	6.5	8.7
Quaker	1.9	2.0	2.0	1.9	2.0
Post	2.8	3.2	2.7	2.4	3.4

Table 2.6 Predicted Payoffs of Quaker and Post in Strategic Form ($1,000,000)

		Quaker: Not Participate	Quaker: Participate
Post	Not Participate	(3.2, 2.0)	(3.7, 1.9)
	Participate	(2.8, 2.2)	(2.7, 2.0)

Note. All payoffs are calculated given that Kellogg's and General Mills are adopting Facts Up Front style FOP labels. In each parentheses, the first number is Post's payoff and the second number is Quaker's.

Table 2.7 Predicted Consumer Yearly Per Capita Intake from Breakfast Cereals

	S0: No Label	S1: Current Practice	S2: All with Bad and Good Labels	S3: All with Bad Labels Only	S4: All with Good Labels Only
	Intake	Intake	Intake	Intake	Intake
Calories	8210	8187.1	7587.2	7003.9	9168.8
Sugar (g)	655	630.9	589.9	559.1	710.3
Saturated Fat (g)	11.2	11.8	11.9	11.3	12.3
Sodium (mg)	12580.0	12665.7	11824.0	10903.4	14116.9
Fiber (g)	96.0	101.4	111.4	91.7	126.2

Table 2.8 Product Attributes of Kellogg's New Product Under Different Scenarios

	N1: All Bad	N2: All Bad but with Good Fiber	N3: All Medium	N4: All Good but with Bad Fiber	N5: All Good
Calories (/oz)	121	121	108	90	90
Sugar (g/oz)	13	13	8	1	1
Saturated Fat (g/oz)	1	1	1	0	0
Sodium (mg/oz)	254	254	180	108	108
Fiber (g/oz)	0	3	2	0	3

Table 2.9 New Product Introduction: Predicted Market Shares Under Current Practice

Firm	Brand	Before New Product Introduction	After New Product Introduction									
			N1: All Bad		N2: All Bad but with Good Fiber		N3: All Medium		N4: All Good but with Bad Fiber		N5: All Good	
		Share (%)	Share (%)	Change	Share (%)	Change	Share (%)	Change	Share (%)	Change	Share (%)	Change
Kellogg's	Frosted Flakes	2.98	3.09	+0.12	3.01	+0.03	3.45	+0.47	3.67	+0.69	3.53	+0.56
Kellogg's	Raisin Bran	1.94	1.96	+0.02	1.71	-0.23	1.83	-0.12	1.73	-0.22	1.52	-0.42
Kellogg's	Froot Loops	1.28	1.75	+0.47	1.73	+0.45	1.64	+0.37	1.50	+0.22	1.48	+0.20
Kellogg's	Rice Krispies	1.15	0.62	-0.53	0.63	-0.52	0.69	-0.46	0.68	-0.47	0.68	-0.47
Kellogg's	Special K Red Berries	1.29	1.88	+0.58	1.85	+0.56	1.97	+0.68	1.83	+0.54	1.80	+0.51
Kellogg's	Apple Jacks	0.92	0.84	-0.08	0.83	-0.08	0.93	+0.02	0.97	+0.05	0.95	+0.03
Kellogg's	Corn Pops	0.82	0.72	-0.10	0.73	-0.09	0.80	-0.02	0.82	-0.00	0.81	-0.01
Kellogg's	Smart Start	0.64	1.05	+0.41	0.94	+0.31	1.05	+0.42	1.02	+0.39	0.94	+0.31
Kellogg's	Frosted Flakes Gold	0.33	0.23	-0.10	0.21	-0.12	0.25	-0.08	0.25	-0.08	0.23	-0.10
Kellogg's	*New Product*	-	*1.44*	-	*1.76*	-	*1.03*	-	*2.63*	-	*4.65*	-
General Mills	Cheerios	3.91	4.28	+0.37	4.08	+0.17	3.98	+0.06	3.68	-0.24	3.09	-0.83
General Mills	Cinnamon Toast Crunch	2.16	2.86	+0.69	2.84	+0.68	2.71	+0.55	2.56	+0.40	2.49	+0.33
General Mills	Lucky Charms	1.71	1.76	+0.06	1.75	+0.05	1.65	-0.05	1.55	-0.16	1.52	-0.19
General Mills	Cocoa Puffs	0.76	0.66	-0.10	0.71	-0.04	0.75	-0.01	0.74	-0.02	0.76	+0.00
General Mills	Reese's Puffs	0.78	1.10	+0.31	1.20	+0.41	1.41	+0.63	1.46	+0.67	1.48	+0.69
Quaker	Cap'n Crunch	0.70	1.14	+0.44	1.19	+0.49	1.28	+0.58	1.25	+0.55	1.30	+0.60
Quaker	Life Cinnamon	0.65	1.11	+0.45	1.05	+0.39	1.08	+0.43	1.10	+0.44	1.19	+0.53
Quaker	Cap'n Crunch Crunchberries	0.65	0.66	+0.01	0.68	+0.02	0.77	+0.11	0.79	+0.14	0.81	+0.15
Quaker	Cap'n Crunch Peanut Butter Crunch	0.47	0.69	+0.22	0.71	+0.24	0.80	+0.33	0.82	+0.36	0.84	+0.38
Post	Honey Bunches of Oats	3.51	3.32	-0.19	3.48	-0.03	3.41	-0.10	3.08	-0.43	3.05	-0.46
Post	Fruity Pebbles	0.71	0.83	+0.12	0.86	+0.14	0.88	+0.17	0.83	+0.12	0.82	+0.11
Post	Cocoa Pebbles	0.52	0.73	+0.21	0.71	+0.20	0.68	+0.16	0.62	+0.10	0.57	+0.05
Kellogg's		11.35	13.58	+2.23	13.42	+2.07	13.65	+2.30	15.10	+3.75	16.60	+5.25
General Mills		9.32	10.66	+1.34	10.58	+1.26	10.50	+1.17	9.98	+0.66	9.33	+0.01
Quaker		2.48	3.60	+1.12	3.62	+1.14	3.94	+1.46	3.97	+1.49	4.14	+1.66
Post		4.74	4.88	+0.14	5.05	+0.31	4.97	+0.23	4.53	-0.22	4.44	-0.30
Total		27.89	32.72	+4.83	32.67	+4.78	33.05	+5.16	33.57	+5.68	34.51	+6.62

Table 2.10 New Product Introduction: Predicted Payoffs ($1,000,000)

Labeling Schemes	Before New Product Introduction	After New Product Introduction				
		N1: All Bad	N2: All Bad but with Good Fiber	N3: All Medium	N4: All Good but with Bad Fiber	N5: All Good
	Payoff	Payoff	Payoff	Payoff	Payoff	Payoff
Kellogg's						
S0: No Label	10.4	13.3	13.0	13.7	**15.4**	15.1
S1: Current Practice	10.9	13.4	13.1	13.9	15.1	**15.7**
S2: All with Bad and Good Labels	11.1	13.4	13.2	13.5	15.0	**16.5**
S3: All with Bad Labels Only	10.5	12.8	12.5	12.8	**14.7**	14.6
S4: All with Good Labels Only	13.0	16.2	16.0	16.8	18.4	**19.6**
General Mills						
S0: No Label	6.8	8.2	8.1	8.0	7.5	7.3
S1: Current Practice	6.8	8.5	8.5	8.4	8.0	7.6
S2: All with Bad and Good Labels	7.0	8.6	8.7	8.6	8.1	7.6
S3: All with Bad Labels Only	6.5	8.3	8.3	8.2	7.8	7.5
S4: All with Good Labels Only	8.7	10.8	10.7	10.6	10.0	9.5
Quaker						
S0: No Label	1.9	4.2	4.3	3.7	4.5	4.5
S1: Current Practice	2.0	4.6	4.7	4.1	4.9	4.8
S2: All with Bad and Good Labels	2.0	4.0	4.0	3.6	4.3	4.2
S3: All with Bad Labels Only	1.9	3.5	3.6	3.3	3.9	4.0
S4: All with Good Labels Only	2.0	4.7	4.7	4.0	5.0	4.8
Post						
S0: No Label	2.8	2.5	2.6	2.5	2.4	2.4
S1: Current Practice	3.2	3.7	3.8	3.7	3.4	3.4
S2: All with Bad and Good Labels	2.7	2.6	2.6	2.5	2.4	2.3
S3: All with Bad Labels Only	2.4	2.0	2.1	2.0	1.9	1.8
S4: All with Good Labels Only	3.4	3.2	3.2	3.2	2.9	2.8

Table 2.11 New Product Introduction: Predicted Impacts on Consumers

Labeling Schemes	Before New Product Introduction			After New Product Introduction																			
				N1: All Bad				N2: All Bad but with Good Fiber				N3: All Medium				N4: All Good but with Bad Fiber				N5: All Good			
	From Existing "Bad" Products	From Existing "Good" Products	Total	From Existing "Bad" Products	From Existing "Good" Products	From New Product	Total	From Existing "Bad" Products	From Existing "Good" Products	From New Product	Total	From Existing "Bad" Products	From Existing "Good" Products	From New Product	Total	From Existing "Bad" Products	From Existing "Good" Products	From New Product	Total	From Existing "Bad" Products	From Existing "Good" Products	From New Product	Total
Calories																							
S0: No Label	4017.4	4192.6	8210.0	5345.7	5499.1	318.2	11163.0	5368.9	5493.3	241.7	11103.8	5610.8	5097.3	275.1	10983.2	5487.8	5059.9	808.5	11356.2	5543.6	4952.8	703.3	11199.8
S1: Current Practice	3532.5	4654.6	8187.1	4313.9	5789.5	474.3	10577.7	4353.0	5665.3	580.9	10599.2	4603.0	5451.0	302.6	10356.6	4579.7	5435.8	644.6	10660.2	4533.9	5100.0	1137.7	10771.5
S2: All with Bad and Good Labels	3456.9	4130.3	7587.2	4209.7	4982.0	450.4	9642.1	4267.9	4921.2	406.5	9595.6	4519.6	4678.7	247.5	9445.8	4468.1	4646.5	647.9	9762.5	4409.3	4333.8	1100.9	9844.0
S3: All with Bad Labels Only	3438.3	3565.6	7003.9	4203.2	4319.8	416.7	8939.7	4235.9	4324.8	322.8	8883.4	4487.7	4075.9	210.9	8774.6	4421.5	4010.3	726.7	9158.4	4441.2	3904.8	700.0	9045.9
S4: All with Good Labels Only	4124.0	5044.8	9168.8	5376.2	6264.6	343.2	11984.0	5415.0	6204.5	315.8	11935.4	5667.8	5788.8	308.5	11765.1	5558.8	5796.3	726.3	12081.5	5512.2	5435.1	1106.5	12053.8
Sugar (g)																							
S0: No Label	429.6	225.4	655.0	563.6	323.3	34.2	921.1	566.0	323.7	26.0	915.7	590.9	299.9	20.4	911.2	577.6	300.4	9.0	887.0	583.4	298.0	7.8	889.2
S1: Current Practice	380.7	250.2	630.9	457.9	333.9	51.0	842.7	461.7	326.2	62.4	850.4	488.0	314.9	22.4	825.3	485.3	318.5	7.2	811.0	480.3	303.8	12.6	796.8
S2: All with Bad and Good Labels	372.0	217.9	589.9	446.6	281.8	48.4	776.8	452.7	278.8	43.7	775.2	479.1	265.4	18.3	762.8	473.4	267.4	7.2	748.0	467.2	253.9	12.2	733.4
S3: All with Bad Labels Only	369.6	189.5	559.1	445.3	246.3	44.8	736.3	448.6	247.2	34.7	730.5	474.9	233.2	15.6	723.8	467.7	232.0	8.1	707.8	469.7	230.0	7.8	707.5
S4: All with Good Labels Only	440.9	269.4	710.3	567.2	360.3	36.9	964.4	571.2	357.4	33.9	962.6	597.4	332.8	22.9	953.0	585.5	337.2	8.1	930.8	580.6	321.2	12.3	914.1
Saturated Fat (g)																							
S0: No Label	9.9	1.3	11.2	13.9	1.8	2.6	18.3	14.0	1.8	2.0	17.8	13.9	2.0	2.5	18.5	13.1	2.1	0.0	15.2	13.3	2.2	0.0	15.5
S1: Current Practice	10.5	1.3	11.8	13.9	1.9	3.9	19.7	14.0	1.9	4.8	20.8	14.3	2.2	2.8	19.3	13.6	2.2	0.0	15.8	13.5	2.3	0.0	15.8
S2: All with Bad and Good Labels	10.5	1.4	11.9	13.2	1.7	3.7	18.7	13.2	1.8	3.4	18.4	13.7	2.1	2.3	18.1	13.0	2.1	0.0	15.2	12.9	2.2	0.0	15.2
S3: All with Bad Labels Only	9.8	1.5	11.3	12.3	1.8	3.4	17.5	12.4	1.8	2.7	16.9	12.8	2.1	2.0	16.8	12.1	2.1	0.0	14.3	12.3	2.2	0.0	14.5
S4: All with Good Labels Only	11.0	1.3	12.3	14.9	2.1	2.8	19.9	16.0	2.3	2.6	21.0	15.1	2.0	2.9	19.9	14.2	2.0	0.0	16.2	14.0	2.1	0.0	16.1
Sodium (mg)																							
S0: No Label	5623.8	6956.2	12580.0	7551.6	8888.3	668.0	17107.9	7595.9	8866.7	507.3	16969.9	7929.8	8323.8	458.5	16712.1	7749.9	8159.1	970.2	16879.2	7840.3	7979.3	844.0	16663.6
S1: Current Practice	4918.8	7746.9	12665.7	6127.8	9331.6	995.6	16454.9	6197.4	9099.4	1219.4	16516.2	6544.5	8876.3	504.3	15925.1	6497.8	8761.2	773.6	16032.6	6449.8	8202.3	1365.2	16017.2
S2: All with Bad and Good Labels	4843.9	6980.1	11824.0	5960.5	8125.4	945.4	15031.4	6048.8	8026.6	853.4	14928.8	6409.1	7730.5	412.4	14552.1	6327.6	7566.3	777.4	14671.4	6260.3	7060.9	1321.0	14642.3
S3: All with Bad Labels Only	4829.6	6073.8	10903.4	5962.5	7104.8	874.6	13941.9	6020.7	7103.9	677.6	13802.3	6380.8	6786.5	351.6	13518.9	6278.9	6590.8	872.0	13741.7	6322.3	6415.9	840.0	13578.1
S4: All with Good Labels Only	5771.2	8345.7	14116.9	7586.9	10085.6	720.5	18393.0	7650.4	9979.8	663.0	18293.1	7999.0	9418.9	514.2	17932.1	7838.7	9301.1	871.6	18011.5	7785.0	8715.7	1327.8	17828.6
Fiber (g)																							
S0: No Label	32.3	63.7	96.0	39.1	83.4	0.0	122.5	39.4	82.9	6.0	128.3	41.0	75.0	5.1	121.0	39.5	74.8	0.0	114.2	39.8	71.5	23.4	134.8
S1: Current Practice	29.1	72.3	101.4	38.1	93.2	0.0	131.4	38.5	86.3	14.4	139.2	42.2	83.0	5.6	130.8	39.3	84.5	0.0	123.8	38.7	75.9	37.9	152.5
S2: All with Bad and Good Labels	34.1	77.3	111.4	41.9	92.2	0.0	134.1	41.9	90.2	10.1	142.1	44.1	84.9	4.6	133.6	43.1	84.1	0.0	127.1	42.1	76.4	36.7	155.1
S3: All with Bad Labels Only	32.0	59.7	91.7	39.0	73.6	0.0	112.6	39.3	73.4	8.0	120.7	41.1	67.8	3.9	112.8	40.2	66.8	0.0	107.0	40.2	63.7	23.3	127.3
S4: All with Good Labels Only	40.6	85.6	126.2	52.5	105.1	0.0	157.6	52.7	103.4	7.8	164.0	54.5	95.1	5.7	155.3	52.9	95.1	0.0	148.0	52.0	86.2	36.9	175.0

Table 3.1 Descriptive Statistics of Major Cereal Products

Firm	Brand	Calories	Sugar (g/oz)	Sat. Fat (g/oz)	Sodium (mg/oz)	Fiber (g/oz)	Protein (g/oz)	Ave. Price ($/oz)	Ave. GRP	Share	Kids
Kellogg's	Frosted Mini-Wheats	96	6	0	3	3	3	0.1439	76.6	4.34%	1
Kellogg's	Frosted Flakes	103	11	0	129	1	1	0.1468	187.3	4.48%	1
Kellogg's	Froot Loops	110	13	1	132	1	1	0.1723	95.9	2.08%	1
Kellogg's	Rice Krispies	108	3	0	254	0	2	0.1993	107.4	1.93%	1
Kellogg's	Apple Jacks	109	12	0	124	0	1	0.1720	112.2	1.63%	1
Kellogg's	Corn Pops	106	13	0	108	0	1	0.1734	68.9	1.78%	1
Kellogg's	Cocoa Krispies	107	10	1	178	1	1	0.1545	30.9	1.10%	1
Kellogg's	Raisin Bran	90	8	0	162	3	3	0.1269	0.0	3.45%	0
Kellogg's	Special K Red Berries	103	9	0	199	1	3	0.2071	34.1	1.74%	0
Kellogg's	Kashi GOLEAN Crunch!	106	7	0	108	4	5	0.1799	53.8	1.54%	0
Kellogg's	Raisin Bran Crunch	99	11	0	110	2	2	0.1486	126.5	1.35%	0
Kellogg's	Special K	106	4	0	202	1	6	0.2136	39.5	1.75%	0
Kellogg's	Smart Start	102	8	0	154	2	2	0.1754	0.1	1.44%	0
Kellogg's	All-Bran	73	4	0	68	8	4	0.1786	36.3	0.35%	0
General Mills	Cinnamon Toast Crunch	121	9	0	196	1	1	0.1630	280.5	3.23%	1
General Mills	Lucky Charms	114	11	0	190	1	2	0.1794	262.6	2.78%	1
General Mills	Cocoa Puffs	112	13	0	149	1	1	0.1784	159.5	1.58%	1
General Mills	Reese's Puffs	121	11	0	187	1	2	0.1746	211.5	1.13%	1
General Mills	Cookie Crisp	112	12	0	159	1	1	0.2039	185.9	1.02%	1
General Mills	Trix	112	12	0	158	1	1	0.1978	194.9	1.10%	1
General Mills	Cheerios	103	1	0	186	3	3	0.1867	152.7	6.37%	0
General Mills	Fiber One	56	0	0	98	13	2	0.2016	0.1	0.79%	0
General Mills	Wheaties	103	4	0	196	3	3	0.1923	1.6	0.58%	0
Quaker	Cap'n Crunch	113	12	1	209	1	1	0.1473	35.5	1.26%	1
Quaker	Cap'n Crunch Crunchberries	113	13	1	196	1	1	0.1513	15.0	1.24%	1
Quaker	Cap'n Crunch Peanut Butter Crunch	116	9	1	208	1	2	0.1568	14.9	0.71%	1
Quaker	Life Cinnamon	104	7	0	134	2	3	0.1408	11.5	1.61%	0
Post	Fruity Pebbles	112	12	0	164	0	1	0.1697	100.2	1.31%	1
Post	Cocoa Pebbles	111	12	1	151	0	1	0.1678	131.5	1.14%	1
Post	Honey-Comb	111	11	0	208	1	1	0.1565	184.8	1.31%	1
Post	Honey Bunches of Oats	112	6	0	140	2	2	0.1508	171.3	6.07%	0
Post	Grape-Nuts	101	4	0	153	2	3	0.1175	0.6	1.36%	0

Table 3.2 Pairwise Frequencies of Joint Promotions

	*K Frosted Mini-Wheats	*K Frosted Flakes	*K Froot Loops	*K Rice Krispies	*K Apple Jacks	*K Corn Pops	*K Cocoa Krispies	K Raisin Bran	K Special K Red Berries	K Kashi GOLEAN Crunch!	K Raisin Bran Crunch	K Special K	K Smart Start	K All-Bran	*GM Cinnamon Toast Crunch	*GM Lucky Charms	*GM Cocoa Puffs	*GM Reeses Puffs	*GM Cookie Crisp	*GM Trix	GM Cheerios	GM Fiber One	GM Wheaties	*Q Capn Crunch	*Q Capn Crunch Crunchberries	*Q Capn Crunch Peanut Butter Crunch	Q Life Cinnamon	*P Fruity Pebbles	*P Cocoa Pebbles	*P Honey-Comb	P Honey Bunches of Oats	P Grape-Nuts
*K Frosted Mini-Wheats	-	2	1	1	1	0	2	1	1	0	0	0	1	1	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	0
*K Frosted Flakes	681	-	3	5	3	2	1	4	1	0	1	1	0	0	0	2	1	0	0	1	3	1	1	0	1	0	1	0	0	1	3	0
*K Froot Loops	481	615	-	2	3	4	0	2	0	0	1	0	0	0	0	2	0	0	0	1	2	0	0	0	1	0	1	0	0	0	0	0
*K Rice Krispies	504	572	444	-	2	2	1	1	0	1	1	0	1	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0
*K Apple Jacks	432	508	433	366	-	2	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
*K Corn Pops	378	446	382	365	374	-	1	2	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
*K Cocoa Krispies	190	203	149	167	133	124	-	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K Raisin Bran	560	549	411	423	362	327	162	-	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
K Special K Red Berries	319	301	235	213	192	171	91	237	-	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
K Kashi GOLEAN Crunch!	159	181	111	116	99	95	51	117	109	-	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
K Raisin Bran Crunch	250	237	174	162	146	127	65	179	134	65	-	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K Special K	300	288	218	204	166	153	87	251	263	85	125	-	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
K Smart Start	277	250	191	207	159	141	79	223	193	84	114	196	-	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0
K All-Bran	90	87	67	66	46	42	30	65	52	23	36	59	62	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
*GM Cinnamon Toast Crunch	390	407	292	290	244	225	113	302	220	134	134	192	158	48	-	1	2	0	0	0	3	0	0	0	0	0	1	0	0	0	1	0
*GM Lucky Charms	378	389	276	278	234	211	109	280	185	133	132	153	152	40	376	-	0	1	0	0	5	0	1	0	0	0	0	0	0	0	1	0
*GM Cocoa Puffs	210	241	189	169	163	145	61	167	106	70	77	103	88	20	212	209	-	0	0	0	3	0	0	0	0	0	0	0	1	1	0	0
*GM Reeses Puffs	232	244	175	180	157	144	65	183	110	76	80	87	77	26	234	236	120	-	1	0	0	0	0	0	0	0	0	0	0	0	0	0
*GM Cookie Crisp	154	150	111	116	92	91	38	106	84	56	51	75	55	14	145	152	84	113	-	0	1	0	0	0	0	0	0	0	0	0	1	0
*GM Trix	166	178	131	135	116	114	42	123	96	48	57	78	62	12	153	143	140	95	52	-	2	0	0	0	0	0	0	0	0	0	0	0
GM Cheerios	558	599	439	445	376	341	156	440	286	191	186	260	230	77	465	449	261	276	187	212	-	2	0	0	2	1	3	1	3	2	5	1
GM Fiber One	35	42	23	24	18	18	10	31	17	13	14	15	16	4	37	38	16	14	9	9	54	-	0	0	1	0	1	0	0	0	0	0
GM Wheaties	100	103	83	77	64	65	28	79	46	24	30	45	34	8	74	83	51	41	36	39	135	9	-	0	0	0	0	0	0	0	0	0
*Q Capn Crunch	189	217	161	148	129	123	58	146	88	68	62	99	79	24	138	121	84	69	51	58	187	14	42	-	0	0	1	0	0	0	0	0
*Q Capn Crunch Crunchberries	153	168	127	130	88	95	43	119	74	42	41	78	61	19	101	94	71	50	44	51	153	13	32	143	-	0	4	1	1	0	0	0
*Q Capn Crunch Peanut Butter Crunch	112	147	111	100	81	74	34	84	55	37	38	56	42	13	78	75	61	42	32	38	128	10	16	133	113	-	0	0	0	0	0	0
Q Life Cinnamon	211	224	179	164	136	128	68	163	103	67	65	93	82	32	140	130	95	71	61	63	206	18	35	152	121	98	-	1	1	0	1	0
*P Fruity Pebbles	211	242	179	169	160	122	53	159	92	66	79	90	92	22	151	146	85	82	53	65	215	14	33	68	72	57	76	-	0	0	0	0
*P Cocoa Pebbles	181	230	162	152	133	114	59	150	90	67	68	89	77	23	139	137	81	81	50	60	199	11	33	77	61	60	68	189	-	1	1	0
*P Honey-Comb	182	213	177	157	143	117	55	147	76	46	66	70	82	29	126	116	77	74	54	57	185	10	42	76	55	52	79	156	138	-	1	0
P Honey Bunches of Oats	518	546	415	396	364	309	146	414	244	167	177	258	220	70	366	354	202	200	136	149	542	48	100	194	160	135	205	284	246	235	-	0
P Grape-Nuts	120	122	97	87	76	61	34	99	69	41	35	55	58	20	97	83	35	45	29	24	125	14	17	41	24	21	48	63	41	34	166	-

Note. The upper triangular part of the matrix gives the frequencies of joint manufacturer coupons, and the lower triangular part gives the frequencies of joint store sales. Products marked with an asteroids are those primarily marketed to children.

Table 3.3 Frequencies of Joint Promotions of Different Firms and Segments

	Joint Store Sale	Joint MFG Coupon
Two of Kellogg's Products	50,070	160
Two of General Mills Products	14,909	116
Two of Quaker Products	2,964	21
Two of Post Products	5,950	36
Two of Kids' Products	34,293	132
Two of Adult/Family's Products	13,584	105
One of Kids' and One of Adult/Family's Product	26,016	96

Note. Promotion frequencies counted based on weekly purchasing data of 32 cereal products from 7 DMAs and 15 major supermarket chains, 2006 to 2008.

Table 3.4 Posterior Means and Credible Intervals of the First Stage MVP Model

Parameter	Posterior Mean	95% Credible Intervals
Price	**-0.461**	(-0.539, -0.358)
Advertising Age 2-11	0.043	(-0.031, 0.124)
Advertising Age 12+	**0.085**	(0.017, 0.162)
Brand Fixed Effects	Yes	
Quarter Fixed Effects	Yes	
DMA Fixed Effects	Yes	
Observations	713,056	

Note. The model was ran for 20,000 iterations with a burn-in phase of 300 and a thinning interval of 10. Coefficients highlighted in bold are significant at 5% level. 7 DMAs include New York, Chicago, Detroit, Atlanta, Boston, Hartford, and San Francisco.

Table 3.5 Estimated Pairwise Correlations Across Cereal Products

	*K Frosted Mini-Wheats	*K Frosted Flakes	*K Froot Loops	*K Rice Krispies	*K Apple Jacks	*K Corn Pops	*K Cocoa Krispies	K Raisin Bran	K Special K Red Berries	K Kashi GOLEAN Crunch!	K Raisin Bran Crunch	K Special K	K Smart Start	K All-Bran	*GM Cinnamon Toast Crunch	*GM Lucky Charms	*GM Cocoa Puffs	*GM Reeses Puffs	*GM Cookie Crisp	*GM Trix	GM Cheerios	GM Fiber One	GM Wheaties	*Q Capn Crunch	*Q Capn Crunch Crunchberries	*Q Capn Crunch Peanut Butter Crunch	Q Life Cinnamon	*P Fruity Pebbles	*P Cocoa Pebbles	*P Honey-Comb	P Honey Bunches of Oats	P Grape-Nuts
*K Frosted Mini-Wheats	1.00																															
*K Frosted Flakes	0.00	1.00																														
*K Froot Loops	-0.01	**0.20**	1.00																													
*K Rice Krispies	**-0.04**	**0.12**	**0.11**	1.00																												
*K Apple Jacks	0.00	**0.22**	**0.43**	**0.10**	1.00																											
*K Corn Pops	-0.01	**0.21**	**0.29**	**0.19**	**0.36**	1.00																										
*K Cocoa Krispies	**0.07**	**0.07**	**0.16**	**0.10**	**0.18**	**0.13**	1.00																									
K Raisin Bran	**0.07**	**0.04**	0.02	0.02	**0.07**	0.03	0.05	1.00																								
K Special K Red Berries	0.02	**-0.12**	**-0.11**	**-0.09**	**-0.07**	**-0.06**	-0.02	0.02	1.00																							
K Kashi GOLEAN Crunch!	-0.05	**-0.09**	**-0.13**	**-0.10**	**-0.16**	-0.07	**-0.14**	-0.05	**0.09**	1.00																						
K Raisin Bran Crunch	**0.05**	-0.01	-0.06	-0.03	-0.05	-0.04	0.05	-0.05	0.03	0.02	1.00																					
K Special K	**-0.05**	**-0.08**	**-0.14**	0.02	**-0.11**	**-0.08**	-0.02	**0.06**	**0.13**	-0.05	0.02	1.00																				
K Smart Start	**0.07**	**-0.11**	**-0.12**	-0.03	**-0.11**	**-0.12**	-0.01	0.03	0.05	**0.07**	**0.14**	**0.16**	1.00																			
K All-Bran	-0.01	-0.08	**-0.13**	-0.05	**-0.17**	**-0.13**	-0.12	0.03	0.03	**0.11**	**0.10**	**0.17**	**0.20**	1.00																		
*GM Cinnamon Toast Crunch	**-0.08**	**-0.08**	**-0.06**	**-0.13**	-0.04	**-0.10**	0.00	**-0.15**	**-0.16**	**-0.11**	-0.02	**-0.10**	**-0.06**	-0.06	1.00																	
*GM Lucky Charms	**-0.09**	**-0.05**	-0.04	**-0.06**	**-0.06**	-0.01	**0.09**	**-0.12**	**-0.09**	**-0.13**	**-0.11**	**-0.11**	**-0.10**	-0.07	**0.25**	1.00																
*GM Cocoa Puffs	**-0.07**	-0.05	**0.07**	-0.05	0.02	0.00	**0.10**	**-0.08**	**-0.14**	**-0.12**	-0.06	**-0.07**	-0.07	**-0.13**	**0.16**	**0.28**	1.00															
*GM Reeses Puffs	**-0.09**	**-0.06**	**-0.06**	**-0.13**	-0.06	-0.04	0.05	-0.06	**-0.11**	**-0.08**	-0.02	-0.05	-0.06	-0.02	**0.20**	**0.25**	**0.24**	1.00														
*GM Cookie Crisp	**-0.07**	**-0.05**	**-0.06**	**-0.13**	0.04	-0.05	0.01	**-0.13**	0.01	-0.01	-0.06	**-0.11**	-0.08	-0.11	**0.17**	**0.26**	**0.20**	**0.26**	1.00													
*GM Trix	**-0.13**	-0.03	0.05	**-0.07**	-0.01	-0.03	0.05	**-0.10**	**-0.11**	-0.08	**-0.11**	-0.05	**-0.10**	-0.08	**0.26**	**0.21**	**0.43**	**0.18**	**0.12**	1.00												
GM Cheerios	**-0.18**	**-0.21**	**-0.16**	**-0.05**	**-0.20**	**-0.14**	**-0.18**	**-0.07**	**-0.09**	**-0.06**	**-0.11**	0.01	**-0.07**	-0.05	-0.02	-0.01	**-0.07**	-0.01	**-0.07**	-0.02	1.00											
GM Fiber One	-0.02	**-0.08**	**-0.13**	-0.07	**-0.10**	-0.08	**-0.15**	-0.03	0.02	**0.11**	-0.03	0.00	**0.11**	**0.10**	-0.07	-0.07	-0.06	-0.04	-0.04	-0.03	-0.03	1.00										
GM Wheaties	-0.03	**-0.14**	**-0.10**	-0.02	**-0.11**	**-0.15**	**-0.12**	**0.07**	-0.01	0.05	0.02	-0.01	-0.04	0.06	-0.04	-0.06	-0.01	0.03	-0.02	-0.01	**0.11**	**0.12**	1.00									
*Q Capn Crunch	**-0.12**	0.04	**0.09**	-0.03	**0.07**	-0.01	-0.02	**-0.10**	**-0.07**	**-0.09**	-0.06	**-0.09**	**-0.09**	-0.08	0.00	0.05	**-0.07**	**0.08**	0.03	0.04	**-0.16**	-0.02	-0.03	1.00								
*Q Capn Crunch Crunchberries	**-0.07**	0.04	0.02	**-0.10**	**0.06**	-0.01	-0.04	**-0.08**	0.01	-0.06	0.00	**-0.11**	-0.02	-0.08	0.02	0.01	0.02	0.02	0.03	-0.01	**-0.16**	-0.08	-0.09	**0.32**	1.00							
*Q Capn Crunch Peanut Butter Crunch	**-0.13**	-0.03	0.00	-0.02	-0.01	-0.05	-0.09	-0.06	-0.06	-0.04	0.05	-0.05	-0.01	-0.02	0.01	**0.07**	0.03	0.01	0.08	0.03	**-0.17**	0.00	0.06	**0.34**	**0.42**	1.00						
Q Life Cinnamon	0.00	**-0.15**	0.00	-0.03	0.00	-0.07	**0.09**	-0.02	-0.01	0.01	0.03	-0.02	-0.03	0.01	0.01	-0.04	**-0.09**	-0.03	-0.06	**-0.08**	**-0.13**	-0.05	-0.01	**0.14**	**0.15**	**0.18**	1.00					
*P Fruity Pebbles	-0.04	0.04	0.02	**-0.08**	0.01	**-0.09**	-0.03	**-0.08**	**-0.14**	**-0.14**	-0.05	**-0.12**	**-0.09**	-0.07	**0.06**	**0.06**	**0.07**	0.00	0.03	0.03	**-0.13**	-0.09	**-0.11**	**0.12**	**0.13**	0.06	0.01	1.00				
*P Cocoa Pebbles	**-0.08**	-0.01	-0.02	**-0.15**	-0.05	**-0.08**	0.04	-0.06	**-0.12**	**-0.09**	-0.07	**-0.10**	**-0.08**	0.01	0.02	**0.06**	0.05	**0.07**	**0.09**	0.01	**-0.14**	-0.06	-0.05	**0.07**	0.03	0.01	-0.05	**0.51**	1.00			
*P Honey-Comb	**-0.07**	0.02	0.04	-0.06	-0.03	0.02	0.00	**-0.10**	-0.05	**-0.13**	**-0.10**	**-0.12**	**-0.12**	-0.11	0.01	**0.07**	0.01	-0.03	**0.08**	0.03	**-0.12**	-0.02	**-0.09**	**0.10**	**0.09**	0.02	-0.01	**0.30**	**0.31**	1.00		
P Honey Bunches of Oats	**-0.05**	**-0.19**	**-0.15**	**-0.13**	**-0.15**	**-0.12**	**-0.10**	**-0.11**	**-0.07**	0.00	-0.04	**-0.08**	**-0.11**	-0.03	-0.03	**-0.18**	**-0.14**	**-0.14**	**-0.07**	**-0.12**	**-0.17**	0.01	**-0.12**	**-0.06**	-0.04	-0.05	**-0.05**	**0.06**	**0.09**	**0.12**	1.00	
P Grape-Nuts	-0.03	**-0.11**	**-0.16**	0.01	**-0.14**	-0.05	-0.07	0.00	-0.05	**0.13**	-0.04	0.01	0.01	0.14	**-0.08**	-0.05	**-0.09**	**-0.10**	**-0.18**	-0.03	0.01	**0.08**	**0.10**	-0.09	**-0.12**	-0.08	0.01	**-0.10**	-0.07	-0.10	**0.07**	1.00

Note. The model was ran for 20,000 iterations with a burn-in phase of 300 and a thinning interval of 10. Estimates of correlation coefficients denoted in bold are significant at 5% level. Products marked with an asteroids are those primarily marketed to children.

Table 3.6 Second Stage Parameter Estimates

Description	(1)	(2)	(3)	(4)
Joint Promotion Effect				
Store Sales	0.611***	0.585***	0.474***	
	(0.065)	(0.062)	(0.058)	
MFG Coupons	0.905***	0.581***	0.633***	
	(0.171)	(0.155)	(0.143)	
Segment Effect				
Two of Kids Cereals			0.131***	0.064***
			(0.010)	(0.014)
Two of Adult/Family Cereals			0.126***	0.053***
			(0.013)	(0.015)
Interactions				
Store Sale*Two of Kids Cereals				0.391***
				(0.100)
Store Sale*Two of Adult/Family Cereals				1.007***
				(0.111)
MFG Coupon*Two of Kids' Cereals				2.802***
				(0.378)
MFG Coupon*Two of Adult/Family Cereals				-0.200
				(0.174)
Manufacturer Effect				
Two of Kellogg's Cereals		0.048**	0.062***	0.044**
		(0.021)	(0.019)	(0.018)
Two of General Mills Cereals		0.171***	0.173***	0.169***
		(0.024)	(0.022)	(0.020)
Two of Quaker Cereals		0.430***	0.424***	0.421***
		(0.043)	(0.039)	(0.036)
Two of Post Cereals		0.257***	0.268***	0.263***
		(0.036)	(0.033)	(0.030)
One of Kellogg's and One of General Mills		-0.042**	-0.035**	-0.036**
		(0.019)	(0.018)	(0.016)
One of Quaker and One of Post		0.049	0.045*	0.037
		(0.030)	(0.027)	(0.025)
One of Kellogg's and One of Quaker		0.008	0.011	0.005
		(0.022)	(0.020)	(0.019)
One of Kellogg's and One of Post		-0.042*	-0.035*	-0.035**
		(0.021)	(0.019)	(0.018)
One of General Mills and One of Quaker		0.029	0.020	0.020
		(0.025)	(0.023)	(0.021)
Intercept	-0.065***	-0.082***	-0.146***	-0.089***
	(0.008)	(0.017)	(0.016)	(0.015)
Observations	496	496	496	496
R-squared	0.236	0.409	0.517	0.593

Note. LHS variables are posterior means of correlation coefficients from the first stage MVP model. All models are corrected for heteroscedasticity using HC3 estimators. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The benchmark section dummy is one of kids cereals and one of adult/family cereals. And the benchmark manufacturer dummy is one of General Mills products and one of Post products.

Table 3.7 Simulated Correlation Changes

Scenario	Description	Average Change
S1	Both Joint Store Sale/MFG Coupon Increased by 20%	0.0105
S2	Both Joint Store Sale/MFG Coupon Equal to 0	-0.0525
S3	Joint Store Sale Increased by 20%	0.0095
S4	Joint MFG Coupon Increased by 20%	0.0010

Figure 1.1 Monthly Cereal Volume Sales (in ounces) Trends of Treatment (Kellogg's/General Mills) and Control (Post/Quaker) Groups

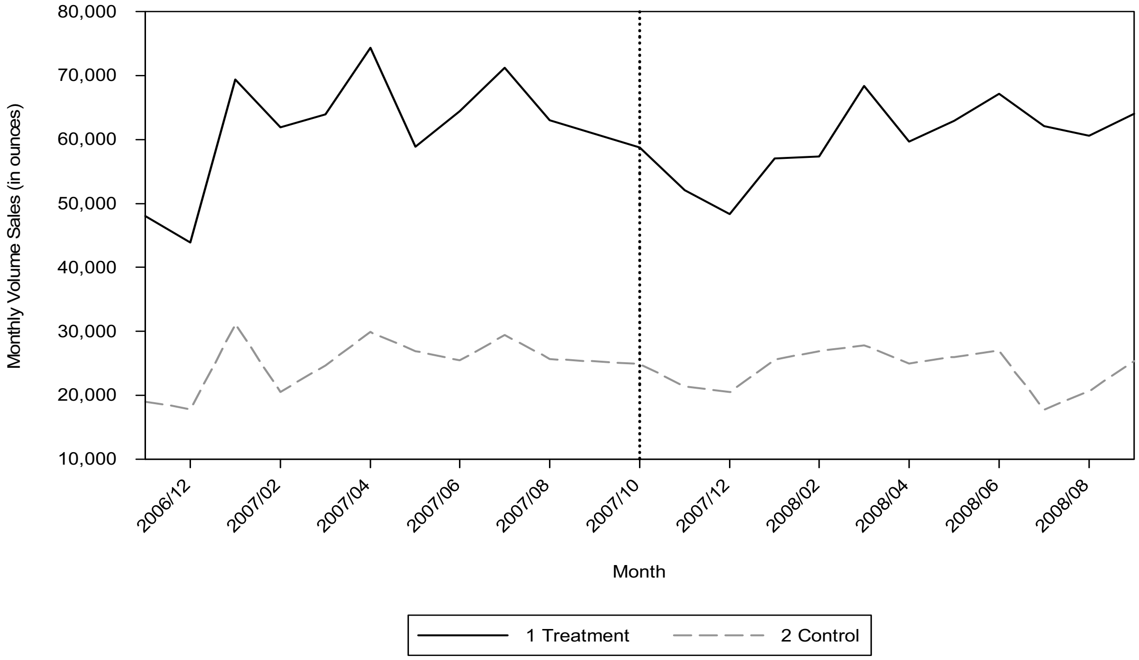


Figure 1.2 Histogram and Kernel Density Estimate of Households' Average Monthly Cereal Volume Purchased (hhvol, in ounces)

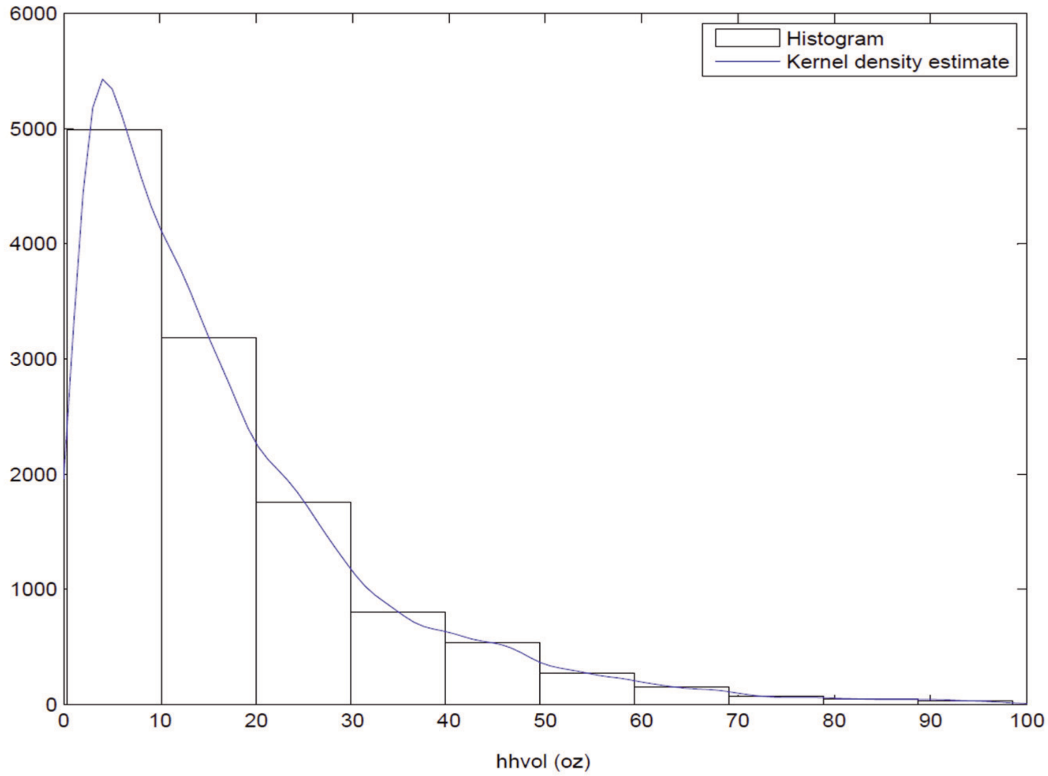
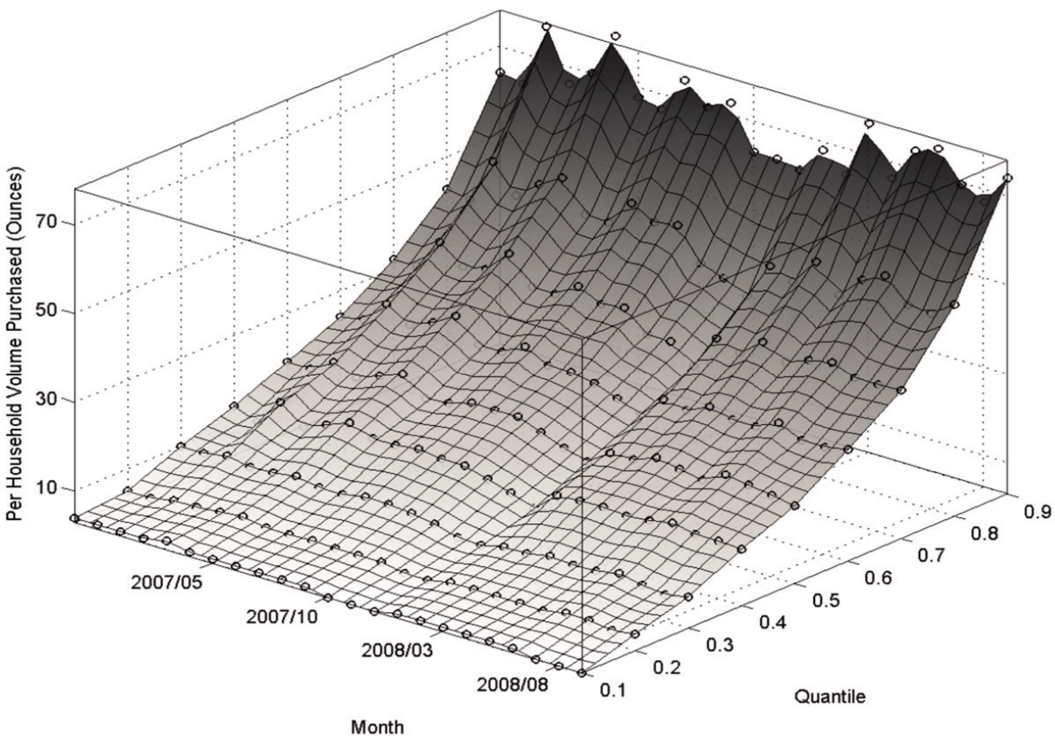


Figure 1.3 Quantiles of Households' Monthly Cereal Volume Purchased (in ounces)

(1) Each Month



(2) Average

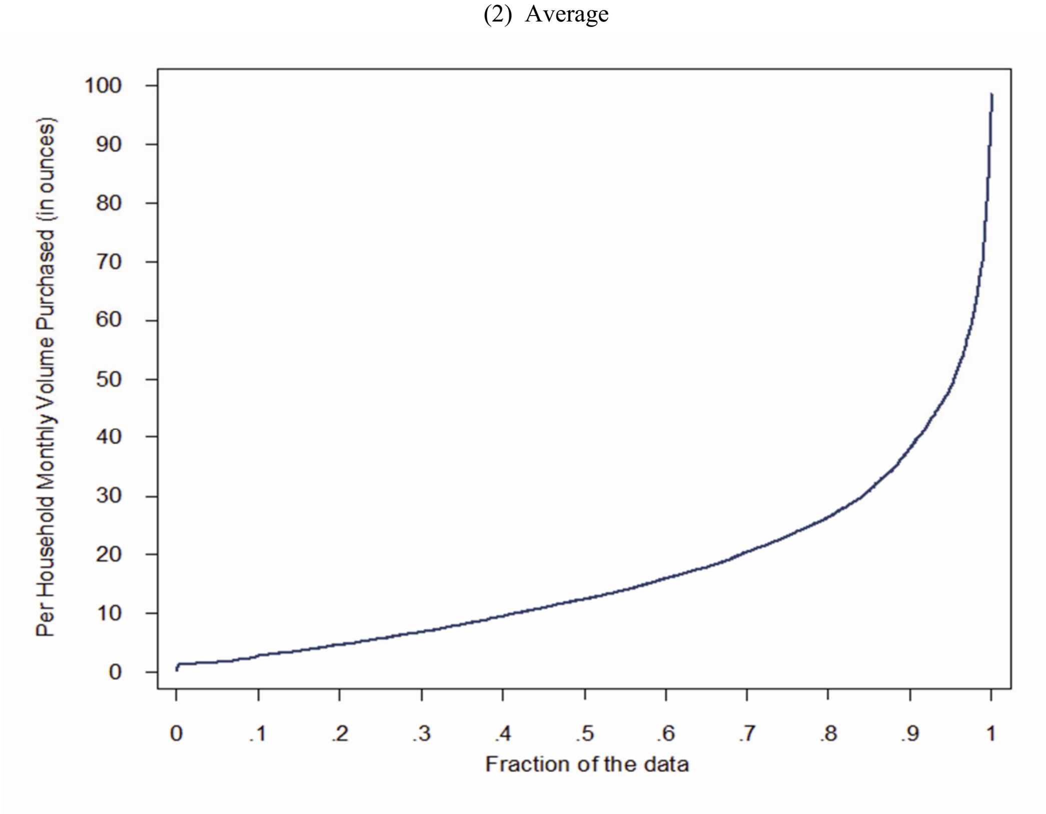
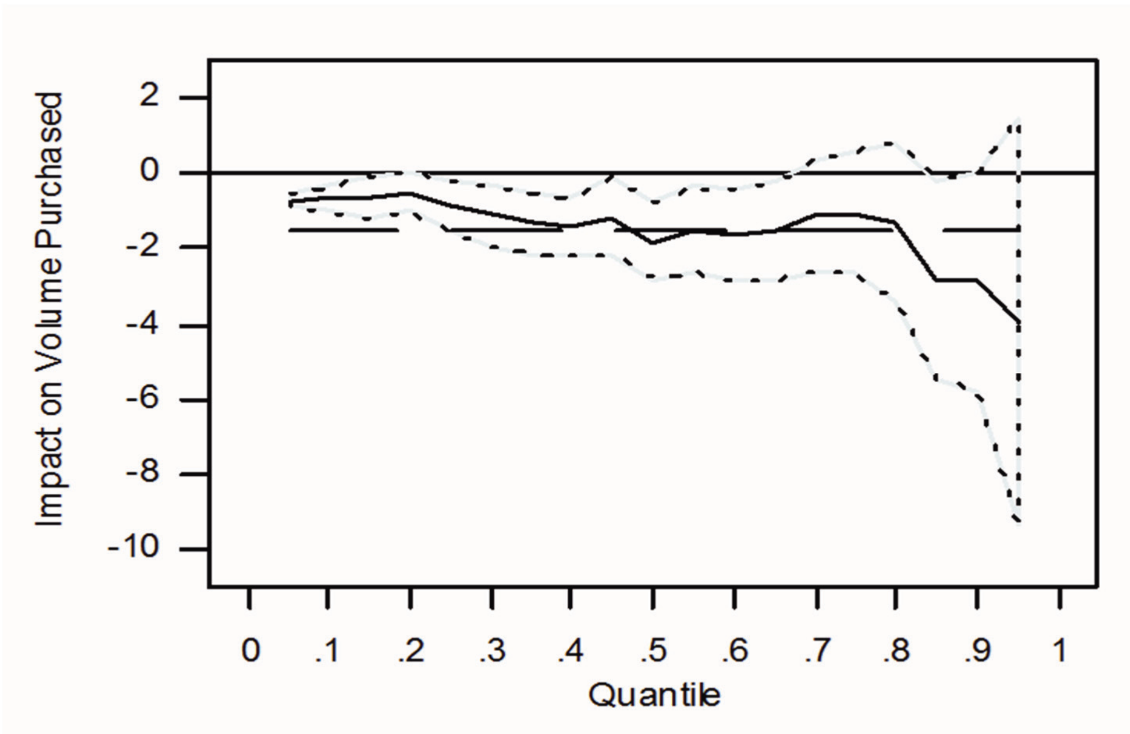


Figure 1.4 Quantile DID Effects on the Distribution of Volume Purchased



Notes: Solid line is the quantile DID effect on volume purchased (results reported in Table 1.4); dotted lines give 95% confidence intervals based on 200 bootstrap replications; dashed line is the mean DID effect (results reported in Table 1.3, Column 1).

Figure 2.1 Market Shares of Major Ready-to-Eat Cereal Manufacturers

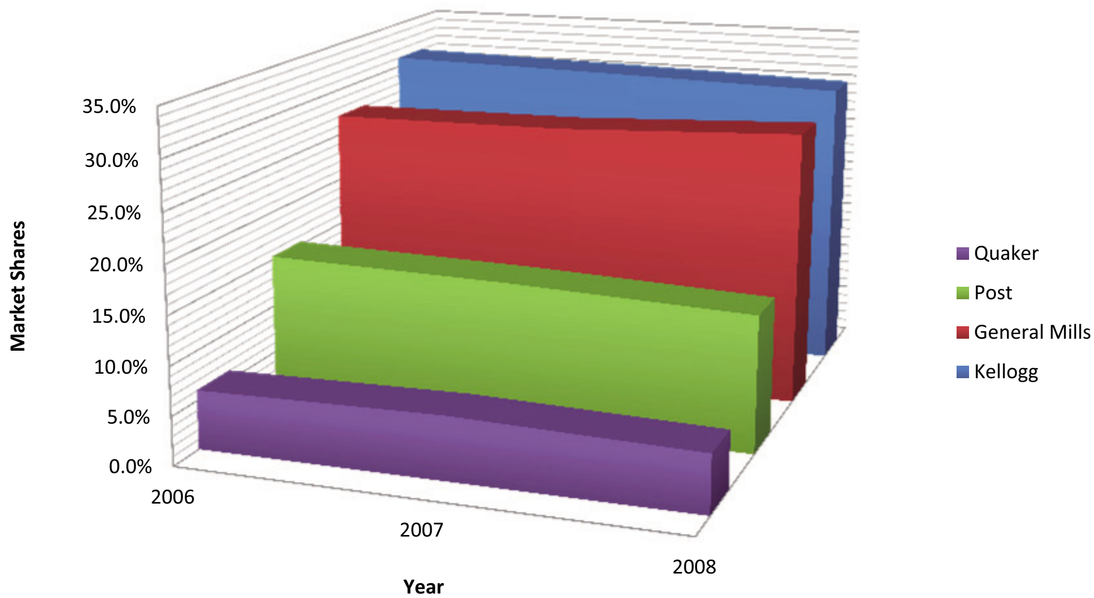


Figure 2.2 Front Packages of Kellogg's Rice Krispies and General Mill's Cheerios

Note. Front packages in 2006 (left), and in 2008 (right) after the implementation of *Nutrition at a Glance* of Kellogg's and *Nutrition Highlights* of General Mills.

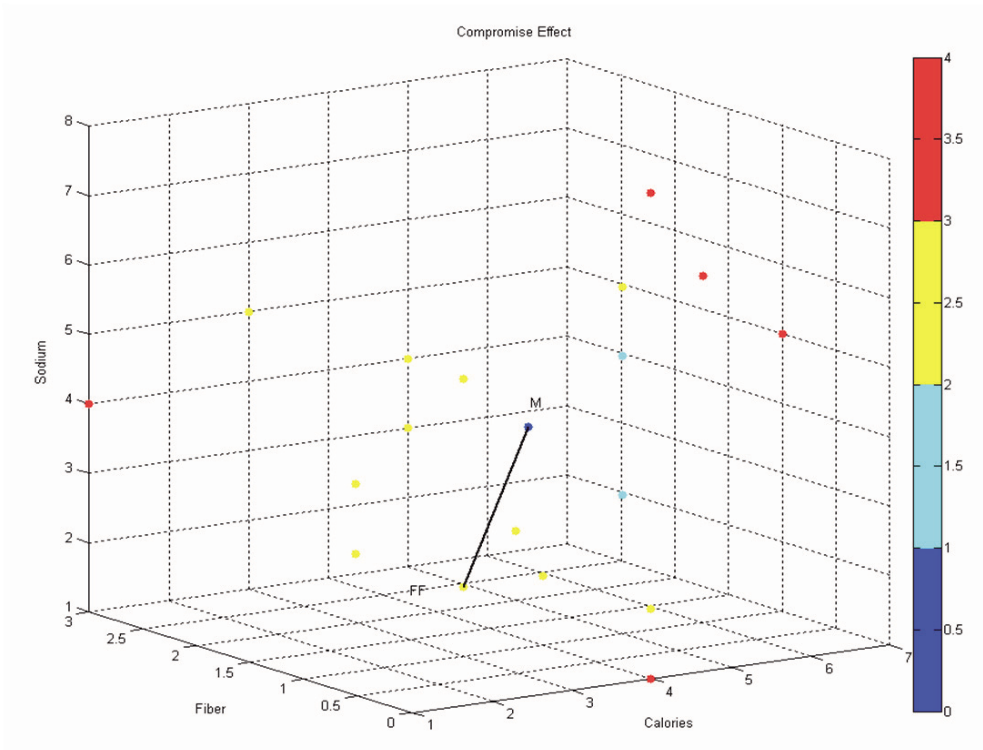
Figure 2.3 Examples of Facts Up Front Style FOP Labels

(a) Kellogg's FOP labels in 2006 (left) and Nutrition at a Glance in 2008 (right).

(b) General Mills' FOP Goodness Corner logos in 2006 (left) and Nutrition Highlights in 2008 (right).

Figure 2.4 Illustrations of Context Variables

(a)



(b)

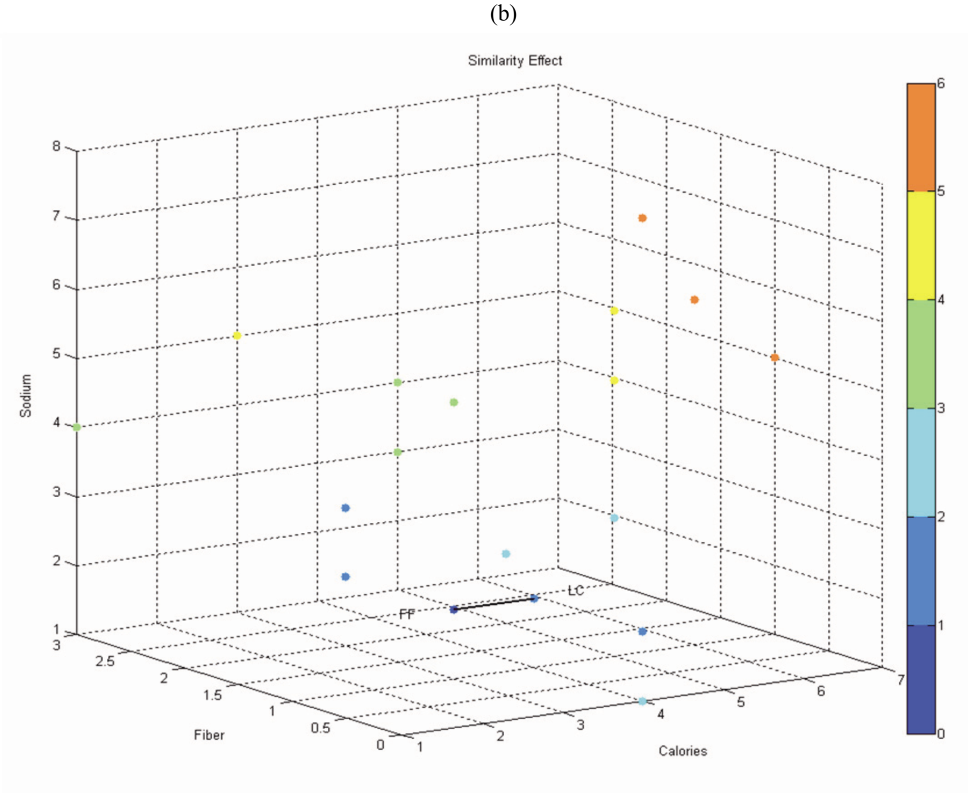


Figure 2.5 Illustrations of New Product Introduction

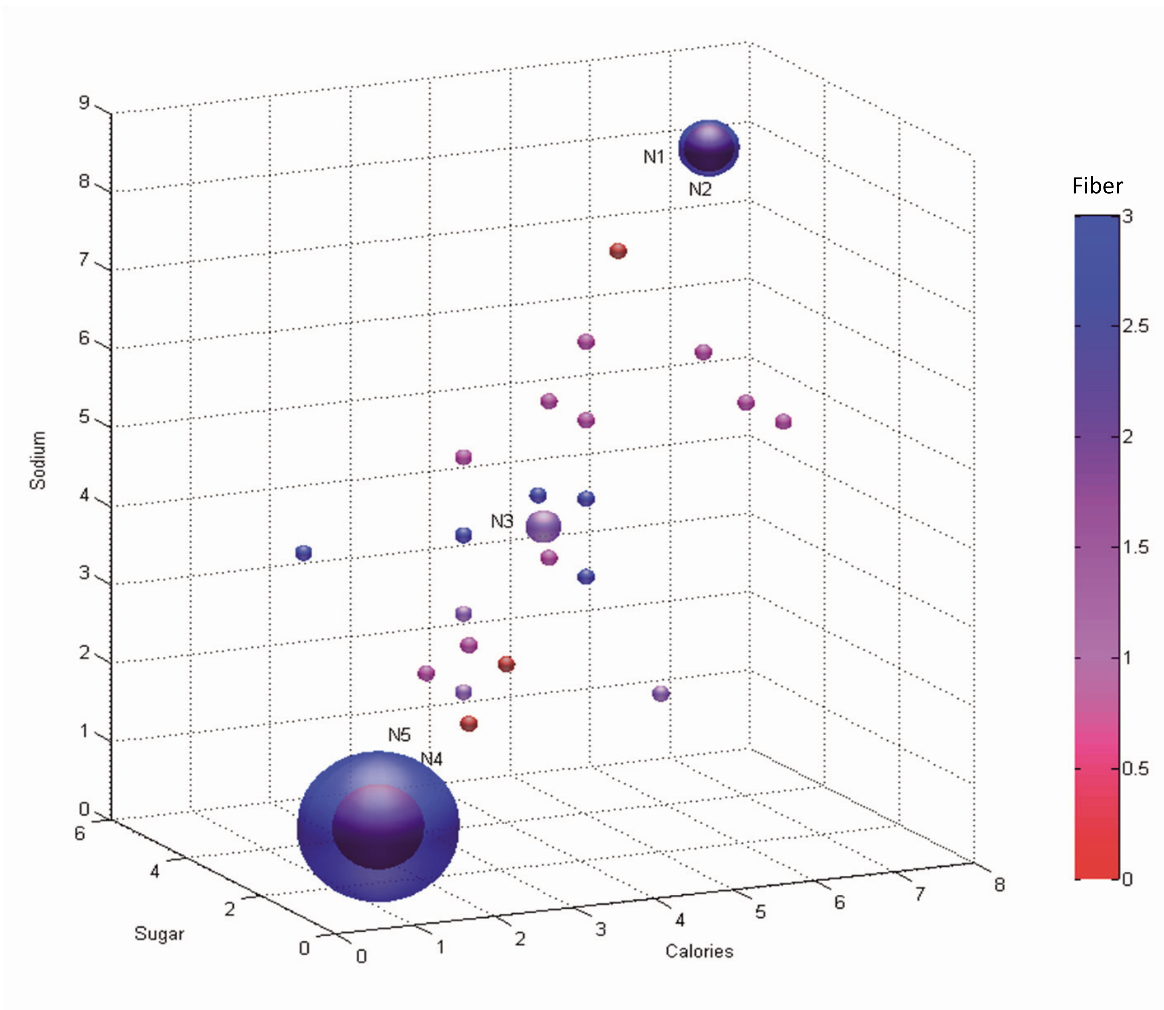


Figure 3.1 Histogram of Cereal Products Purchased in a Shopping Trip

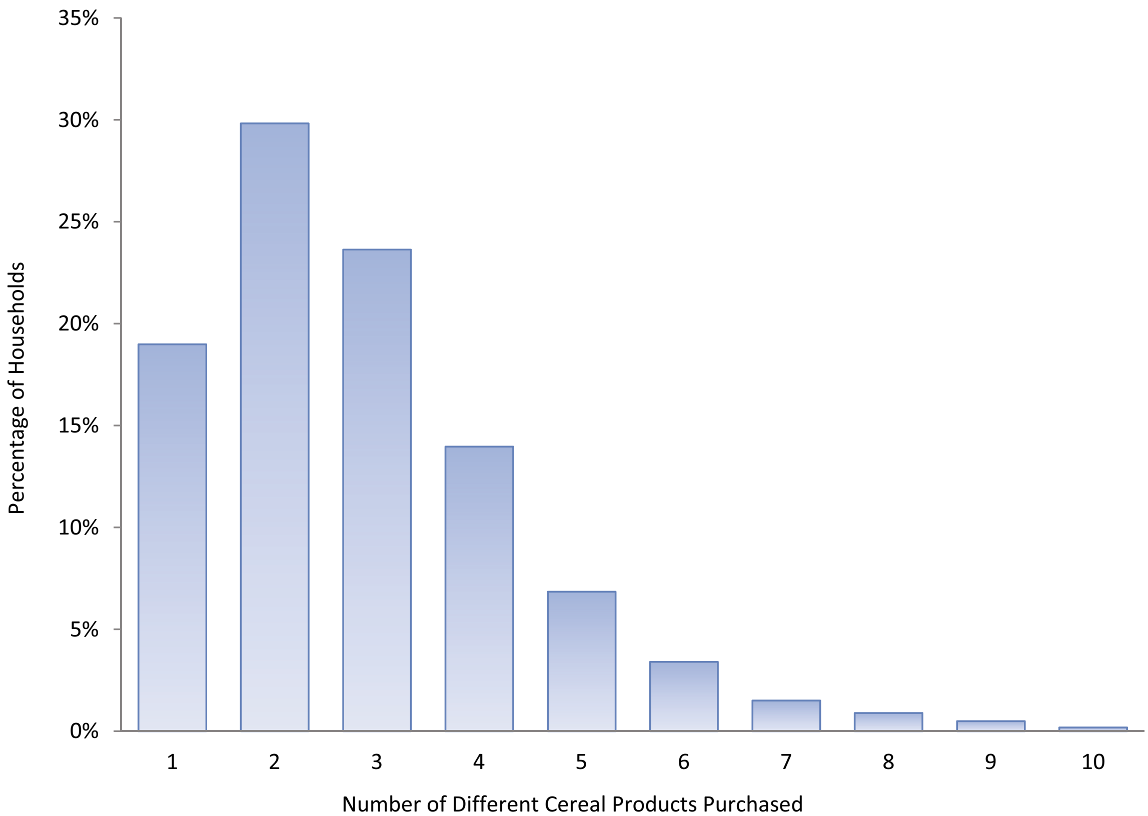


Figure 3.2 Examples of Cereal Products Joint Promotions

(a) Joint Store Sales

(b) Joint Manufacturer Coupons

Note. Photo (a) shows a store sale that Kellogg's Corn Flakes, Rice Kripsies, Cocoa Krispies, Apple Jacks, Mini Wheats, Raisin Bran, Corn Pops, Krave, Frosted Flakes and Froot Loops are for $1.78 each (source: http://queenbeecoupons.com/). Photo (b) gives two examples of Kellogg's manufacturer coupons, both are valid when two packages are purchased together (source: http://www.smartcouponing.com/).

Figure 3.3 Percentage Sales of Breakfast Cereals at Major Supermarket Chains in Sample

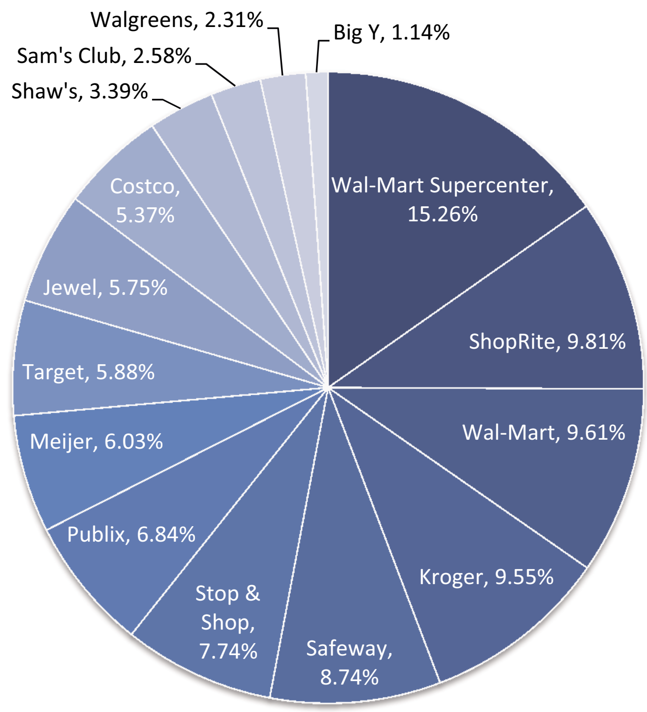
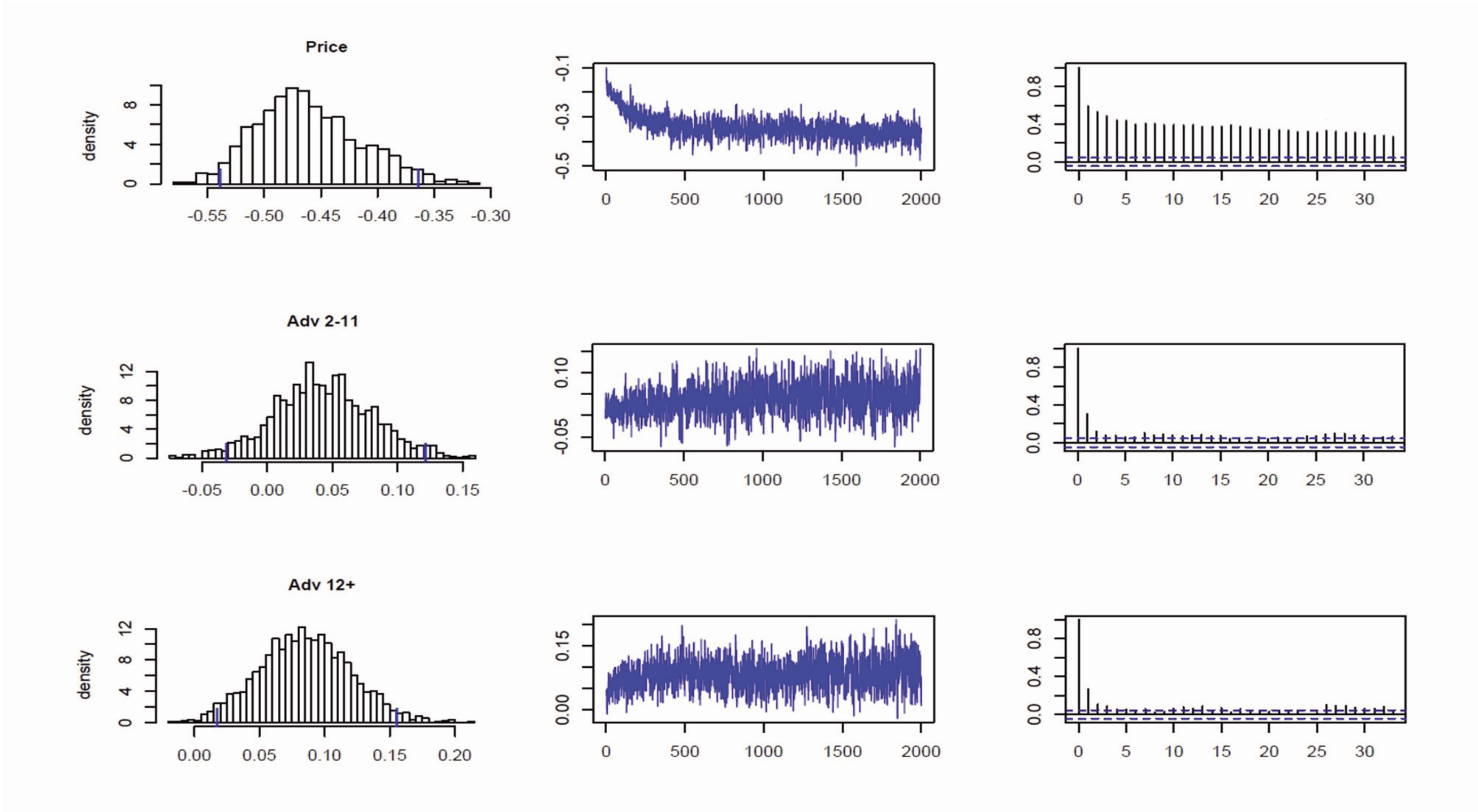


Figure 3.4 Posterior Distributions of Major Parameters



Note. Results are from a sequence of 20,000 draws with a burn-in period of 300, and every 10th draw is taken. For each parameter, the left panel plots the marginal posterior distribution (the red line denotes the mean of posterior, yellow lines denote the numerical standard errors, and green lines denote the 95% credible intervels), the middle panel is the marginal trace plot of MCMC samples, and the right panel shows the autocorrelation functions (ACFs).

Figure 3.5 Estimated Bivariate Correlations Heat Map from MVP Model

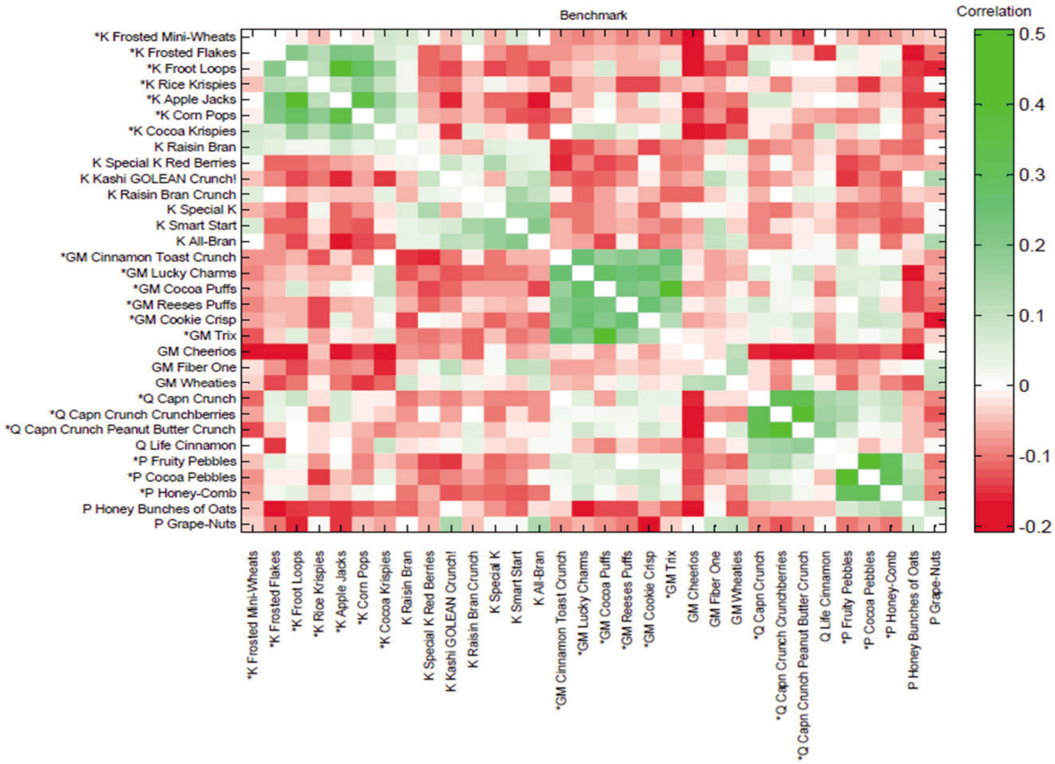
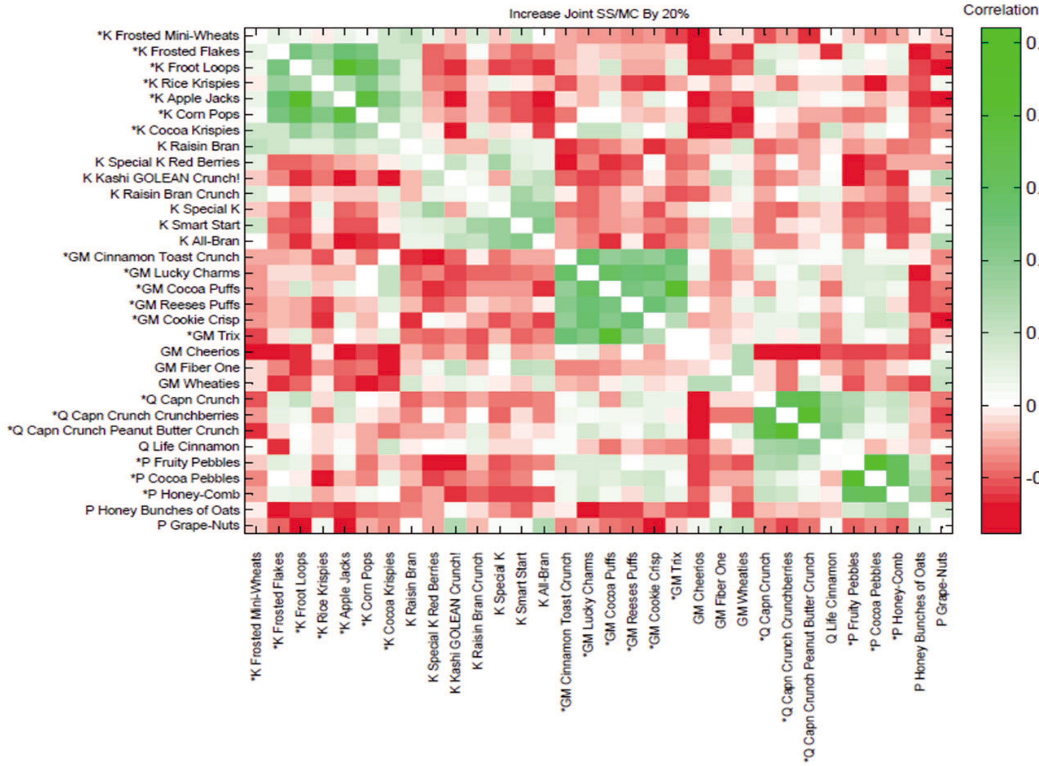


Figure 3.6 Simulated Correlation Heat Map

S1: Both Joint Store Sale/MFG Coupon Increased by 20%



S2: Both Joint Store Sale/MFG Coupon Equal to 0